CHAPTER ONE

INTRODUCTION

1.1 Introduction

Magnetic Resonance Image (MRI) is an imaging method commonly used in medical setting to generate high quality images and provide more effective information of the inside of the human body.[1, 2] It presents the clinician with a number of corresponding quick, precise and flexible diagnostic tools. Magnetic Resonance Image is supposed to be very potential for precise measurement of organ anatomy in a simply way. It is very important to obtain correct image in order to make easy the accurate observations for a given application in medical image processing. [3]

Magnetic Resonance Image (MRI) is a notable medical imaging technique that has proven to be particularly valuable for examination of the soft tissues in the body. MRI is an imaging technique that makes use of the phenomenon of the spin resonance. Since the discovery of MRI, this technology has been used for many medical applications. Because of the resolution of MRI and the Technology being essentially harmless it has emerged as the most accurate and desirable imaging technology. [4]

Image denoising can be considered as a preprocessing step or as a complete process. In the first case, the image denoising is used to improve the accuracy of various image processing algorithms such as registration or segmentation. Then, the quality of the artifact correction influences performance of the procedure. In the second case, the noise removal aims to improving the image quality for visual inspection. The preservation of relevant image information is important, especially in a medical context.

1.2 Problem Statement

In medical image processing, it is very vital to obtain exact images to facilitate accurate explanation for the known request. Low image quality is an obstacle for effective feature extraction, analysis, recognition and quantitative measurements. Therefore, there is a fundamental need of noise reduction from medical images.

Denoising is the process of removing noise in the images, de-noising of magnetic resonance (MR) images remains a critical issue, spurred partly by the necessity of trading-off resolution, signal to noise ratio (SNR), and university quality index (UQI) which result in images that still exhibit significant noise levels. [5]

Understanding the spatial distribution of noise in an MR image is critical to any attempt to estimate the underpinning signal. The investigation of how noise is distributed in MR images (along with techniques proposed to ameliorate the noise) has a long history. The Rician model was proposed as a more universal model of noise in MR images. Reducing noise has always been one of the standard problems of the image analysis. The success of many analysis techniques such as segmentation, classification depends mainly on the image being noiseless.

1.3 Objectives

General objective:

The aim of the research is propose a new scheme technique to reduction Rician noise from MR image.

Specific objective:

- Evaluate of MR image denoising filters.

- Evaluate the proposed technique using statistical parameters used for analyzing the denoised image.
- Obtained the good technique for MR images denoising by compared the proposed technique with some denoising filters.

1.4 Research Plan

The organization of thesis is a follow. In the following chapter the background of MRI and explain how noise is distributed in magnetic resonance image, then have a discussion about statistical parameters that used to evaluate the image (mean square error (MSE), signal to noise ratio (SNR), university quality index (UQI)) and method noise. The end of this chapter gives explanation of image denoising overview. Literature review in chapter 3, Study of MR image denoising filters in chapter 4, in this chapter estimate of different filtering method and compare between them using image metrics. In chapter 5 explain the proposed, the algorithm that used and evaluate the proposed method by make comparison between it and the different filtering method that explain in chapter 4. And finally confer the conclusion and future work to be done in chapter 6.

CHAPTER TWO

BACKGROUND

2.1 Introduction

Magnetic resonance imaging (MRI), or nuclear magnetic resonance imaging (NMRI), is primary a medical imaging technique most commonly used in radiology to visualize detailed internal structure and limited function of the body. MRI provides much greater contrast between the different soft tissues of the body than computed tomography (CT) dose, making it especially used in neurological (brain), musculoskeletal, cardiovascular, and ontological (cancer) imaging. Unlike CT, it uses no ionizing radiation, but uses a powerful magnetic field to align the nuclear magnetization of (usually) hydrogen atoms in water in the body. [5]

Radio frequency (RF) fields are used to systematically alter the alignment of this magnetization, causing the hydrogen nuclei to produce a rotating magnetic field detectable by the scanner. This signal can be manipulated by additional magnetic field to build up enough information to construct an image of the body. A radiofrequency transmitter is briefly turned on, producing an electromagnetic field. In simple terms, the photons of this field have just the right energy, known as the resonance frequency, to flip the spin of the aligned protons. As the intensity and duration of the field increases, more aligned spins are affected. After the field is turned off, the protons decay to the original spin-down state and the difference in energy between the two states is released as a photon. It is these photons that produce the signal which can be detected by the scanner. The frequency at which the protons resonate depends on the strength of the magnetic field. As a result of conservation of energy, this also dictates the frequency of the released photons. [6]

An image can be constructed because the protons in different tissues return to their equilibrium state at different rates. By changing the parameters on the scanner this effect is used to create contrast between different types of body tissue or between other properties, as in FMRI and diffusion MRI. Contrast agents may be injected intravenously to enhance the appearance of blood vessels, tumors or inflammation. Contrast agents may also be directly injected into a joint in the case of arthrograms, MRI images of joints.

Unlike CT, MRI uses no ionizing radiation and is generally a very safe producer. Nonetheless the strong magnetic fields and radio pulses can affect metal implants, including cochlear implants and cardiac pacemakers. In the case of cardiac pacemakers, the results can sometimes be lethal, so patients with such implants are generally not eligible for MRI.

MRI is used to image every part of the body, and is particularly useful for tissues with many hydrogen nuclei and little density contrast, such as the brain, muscle, connective tissue and most tumors. In clinical practice, MRI is used to distinguish pathologic tissue (such as brain tumors) from normal tissue. One advantage of an MRI scan is that it is believed to be harmless to the patient. It uses strong magnetic fields and non-ionizing radiation in the radio frequency range. Compare this to CT scans and traditional X-rays which involve doses of ionizing radiation and may increase the risk of malignancy, especially in a fetus. While CT provides good spatial resolution (the ability to distinguish two structures an arbitrarily small distance from each other as separate), MRI provides comparable resolution with far better contrast resolution (the ability to distinguish the differences between two arbitrarily similar but not identical tissues). The basis of the ability is the complex library of pulse sequences that the modern medical MRI scanner includes, each of which is optimized to provide image contrast based on the chemical sensitivity of MRI.

2.2 Noise

The limiting factor for many MR examinations is noise. We can, for example, not directly detect substances in vivo in concentrations below a few millimolars on a reasonable timescale, because the signal is drowned by noise.The noise can be physiological (pulse, respiration, movement), but even if the patient is lying completely still, there exists an upper limit for the image quality achievable in a given period. In the absence of physiological noise and under a couple of other assumptions (which are rarely completely fulfilled), the signal to noise ratio is proportional to the voxel size and the square root of the time it has taken to acquire the image. [7]

It is essential to realize that the signal-to-noise ratio is not dependent on the number of voxels in the image. If you double the matrix (points along one side of the image) and the field-of-view it will typically imply that the signal-to-noise ratio is increased by a factor of √2 because the Measuring time is thereby typically doubled while the voxel size remains unaltered. That it may only be extra air that is included by the expanded field-of-view is irrelevant, and the noise level is not affected by the fact that 4 times as many voxels are being measured. [7]

Insofar as the scanner is well functioning, the electronics is not the primary source of noise. Instead, that is the random motion of charged particles (ions) in the patient. When charged particles diffuse, they emit random radio waves as they change their direction of motion. The higher the temperature and conductivity of a material, the more noise it emits.

Thermal noise is evenly distributed despite the fact that it is emitted almost only from within the patient, who may only fill part of the image area. This is caused by the noise not being an MR signal, and the gradient-induced spatial coding of the signal is therefore not affecting the noise. Instead, the noise is received in a steady stream during the entire measurement and it is therefore evenly spread over k-space and consequently also evenly over the MR image. [7]

The noise from patients cannot be avoided, but we can, to some extent, avoid measuring it. The idea is to use a small coil that only detects noise from a small area of the patient (a surface coil, for example). It is a common (but non-essential) misconception that using a small coil primarily enhances the signal-to-noise-ratio through its improved sensitivity to signal. Improved signal sensitivity, however, also increases sensitivity to noise that is generated in the same regions of the body. Improving the sensitivity therefore does not by itself improve the signal-to-noise ratio. Instead, the surface coil limits the noise by being sensitive to a smaller part of the body, of size similar to that of the surface coil. A small surface coil only detects the noise (and signal) from a small part of the body, and this noise appears evenly distributed over the entire image. The surface coil therefore improves the signal-to-noise ratio by reducing the sensitivity to distant noise sources. These effects are well described by Redpath in The British Journal of Radiology, 71:704-7, 1998, for example. [7]

Noise removal is the process of removing noise from a signal. Noise reduction techniques are theoretically comparable regardless of the signal being processed. Image denoising is often used in the field of publishing or photography where an image was degraded somehow but needs to be enhanced before it can be printed. Denoising is playing an important role in Medical image enhancement also. [8]

Retrieving a high quality MR Image for a medical diagnostic is critical, because it injures human more if we pass high level Magnetic resonance sound to take the image. So denoising of magnetic resonance (MR) images is a challenging issue. MR images are normally corrupted by thermal noise, sample resolution, etc. Understanding the spatial distribution of noise in an MR image is very difficult to any attempt to calculate approximately the true signal. The investigation of how noise is distributed in MR images is chronological. [8]

2.3 Image Enhancement

The principal objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application. [9]

Image enhancement, which is one of the significant techniques in digital image processing, plays an important role in many fields, such as medical image analysis, remote sensing, high definition television, hyper spectral image processing, industrial X-ray image processing, microscopic imaging etc. Image enhancement is a processing on image in order to make it more appropriate for certain applications. [10] It is mainly utilized to improve the visual effects and the clarity of the image or to make the original image more conducive for other automated processes. Generally an image may have poor dynamic range or distortion due to the poor quality of the imaging devices or the adverse external conditions at the time of acquisition and so on.

The word specific is important, because it establishes at the outset that the techniques discussed in this thesis. Thus, the method or technique that is quite useful for enhancing MR images. Regardless of the method used, however, image enhancement is one of the most interesting and visually appealing areas of image processing. Image enhancement approaches fall into two broad categories: spatial domain methods and frequency domain methods. The term spatial domain refers to the image plane itself, and approaches in this category are based on direct manipulation of pixels in an image. Frequency domain processing techniques are based on modifying the Fourier transform of an image. Enhancement techniques based on various combinations of methods from these two categories are not unusual. There is no general theory of image enhancement. When an image is processed for visual interpretation, the viewer is the ultimate judge of how well a particular method works. Visual evaluation of image quality is a highly subjective process, thus making the definition of a “good image” an elusive standard by which to compare algorithm performance. When the problem is one of processing images for machine perception, the evaluation task is somewhat easier. For example, in dealing with a character recognition application, and leaving aside other issues such as computational requirements, the best image processing method would be the one yielding the best machine recognition results. However, even in situations when a clear-cut criterion of performance can be imposed on the problem, a certain amount of trial and error usually is required before a particular image enhancement approach is selected.

Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted with noise. The received image needs processing before it can be used in applications. Image denoising involves the manipulation of the image data to produce a visually high quality image.

2.4 Noise Properties of MR Data

The raw MRI data consists of complex valued samples with real and imaginary parts that can each be modeled as the summation of deterministic and Gaussian random noise components. [11]

After reconstruction by inverse Fourier transformation, the real and imaginary data are still corrupted with Gaussian white noise because of the orthogonally of the Fourier transform. However, it is common practice to transform the complex valued images into magnitude and phase images. [11, 12] The magnitude image is formed by calculating the magnitude, pixel by pixel, from the real and the imaginary images. This is a nonlinear mapping and therefore the noise distribution is no longer Gaussian and the noise within each pixel belongs to the Rician distribution. [13, 14] This distribution form depends in a complex manner on the value of the means of the real and imaginary part distributions, which are unknown (in fact their values represent the solution for the denoising problem). The Rician distribution is far from being Gaussian for small SNR ($A/\sigma \leq 1$). For ratios as small as $A/\sigma = 3$, however, it starts to approximate the Gaussian distribution. A special case of the Rician distribution is obtained in image regions where only noise is present, i.e., $A = 0$, which reduces to the known the Rayleigh distribution. Since practical acquisitions of tissue signals involve A/σ that is greater than 3, it is possible to use the Gaussian white noise as a good model for the type of noise encountered in the MRI magnitude images.

In the image denoising process, information about the type of noise present in the original image plays a significant role. Typical images are corrupted with noise modeled with a Gaussian.

2.5 Gaussian noise

Gaussian noise is evenly distributed over the signal. [15] This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian distribution, which has a bell shaped probability distribution function given by,

$$F(g) = \frac{1}{\sqrt{\text{٢}\Pi\sigma^2}} e^{-(g-\mu)^2/2\sigma^2} \qquad (2\text{-}1)$$

Where g represents the gray level, μ is the mean or average of the function and σ is the standard deviation of the noise. Graphically, it is represented as shown in Figure 2.1. When introduced into an image, Gaussian noise with zero mean and variance as 0.05 would look as in Image 2.1[16] Image 2.2 illustrates the Gaussian noise with mean (variance) as 1.5 (10) over a base image with a constant pixel value of 100.

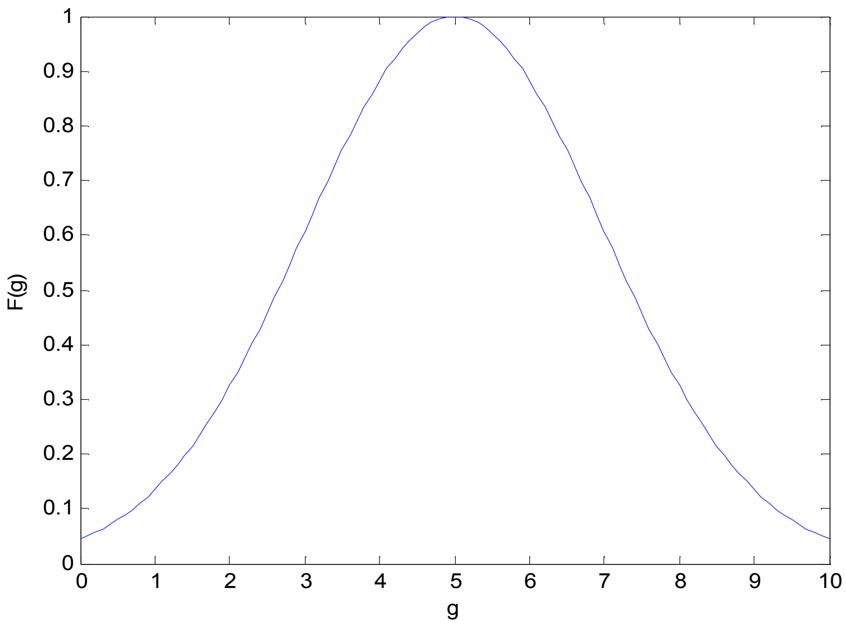

Figure 2.1: Gaussian distribution.

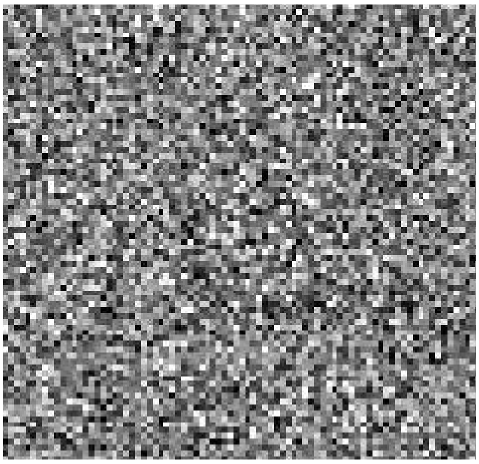

Image 2.1: Gaussian noise
(Mean=0, variance 0.05)

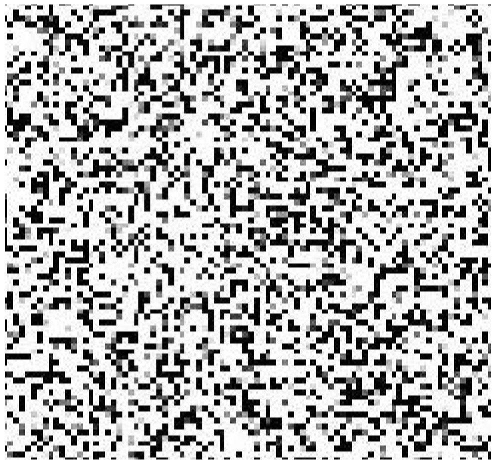

Image 2.2: Gaussian noise
(Mean=1.5, variance 10)

2.6 Image Quality Evaluation Metrics

The quality of an image is examined by objective evaluation as well as subjective evaluation. For subject evaluation, the image has to be observed by human expert. The human visual system (HVS) is so complicated that is not yet modelled properly. There for, in addition to objective evaluation, the image must be observed by a human expert to judge its quality.

To quantify the performance, the noise reduction method, various measures may be used. The commonly preferred measures are mean squared error (MSE), signal to noise ratio (SNR) [17] and university imag quality index (UQI), which can be evaluated as a function of the original, $g_{i,j}$, and the denoised, $f_{i,j}$, the metrics used in our study are defined as Follows:

(a) The mean square error (MSE), which is the squared error averaged over an $M \times N$ window: [10]

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{M} (g_{i,j} - f_{i,j})^2 \qquad (2\text{-}2)$$

(**b**) The signal-to-noise ratio (SNR) is given by: [18]

$$SNR = 10\log 10 \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (g^2 i,j + f^2 i,j)}{\sum_{i=1}^{M} \sum_{j=1}^{N} (gi,j - f\,i,j)} \qquad (2\text{-}3)$$

(**c**) The university quality index (UQI)

Objective image quality measures play important roles in various image processing applications. [19] The university quality index measurement approach does not depend on the images being tested, the viewing conditions or the individual observers. More importantly, it must be applicable to various image processing applications and provide meaningful comparison across different types of image distortions.

Let $x = \{x_i | i = 1,2,\ldots, N\}$ and $y = \{y_i | i=1,2,\ldots,N\}$

Be the original and the test image signals, respectively. The university quality index is defined as:

$$UQI = \frac{4\sigma_{xy}\, \dot{x}\dot{y}}{(\sigma_x^2 + \sigma_y^2)\,[(\dot{x})^2 + (\dot{y})^2]} \qquad (2\text{-}4)$$

Where

$$\dot{x} = \frac{1}{N} \sum_{i=1}^{N} x_i \quad , \quad \dot{y} = \frac{1}{N} \sum_{i=1}^{N} y_i$$

$$\sigma_x^2 = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \dot{x})^2 \quad , \quad \sigma_y^2 = \frac{1}{N-1} \sum_{i=1}^{N} (y_i - \dot{y})^2$$

$$\sigma_{xy} = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \dot{x})(y_i - \dot{y})$$

The dynamic range of UQI is [-1, 1], the best value equal 1.

2.7 Method Noise

Let u be the original image and D_h a denoising operator depending on *h.* then we define the method noise of u as the image difference. [20]

$$(D_h, u) = u - D_h(u) \qquad (2\text{-}5)$$

This method noise should be as similar to Gaussian white noise as possible if the denoising operator preserves the image features.

Four criteria can and will be taken into account in the comparison of denoising methods:

1- A display of typical artifacts in denoised images.

2- A formal computation of the method noise on smooth images, evaluating how small it is in accordance with image local smoothness.

3- A comparative display of the method noise of each method on MR images with five different levels of noise.

4- A classical comparison receipt based on noise simulation: it consists of taking a good quality image, adding rician noise with known σ, and then computing the best image recovered from the noisy one by each method.

2.8 The Image Denoising

Image denoising represents one of the most common tasks of image processing. Several techniques have been developed in the last decades to face the problem of removing noise from images, still preserving the small structures from an excessive blurring. [21]

Denoising means minimize the noise in homogenous area without degrading the image details. Denoising is commonly used for post processing method like restoration, segmentation, classification, pattern analysis and others. [22] Conventionally, noise images have to undergo pre-processing step before being subjected further specifies to analysis. Filtering algorithm is the most common method used to remove the noise as preprocessing. In medical imaging, image filtering algorithm technique is used to enhance image quality, increase visibility which helps in the diagnostic process. [23] However those methods are only for filtering for noise removal and applied the further task on the images as image segmentation.[24] Denoising based segmentation method is proposed to be used to remove the noise and at the same time segment the image into several significant regions.

A novel class of nonlinear filter for image processing known as order statistics (OS) filter. [25] This filter is used for reduction of white noise, signal-dependent noise, and impulse noise. Another filter known as signal adaptive median filter performs better than other nonlinear adaptive filters for different kinds of noise.[26] The adaptive averaging shows poor performance in the presence in the presence of impulsive noise and dose not remove noise close to the edges.[27] The filtering scheme cannot suppress the impulsive noise sufficiently, but can preserve the edge better than the mean filter.[28] It is claimed that decision-based order statistics filters can reduce both impulsive and non-impulsive noise and can also enhance blurred edges better than many other OS filters.[29] An adaptive filtering algorithm for the class of stack filters.[30, 31] Adaptive neural filter removes various kinds of noise such as Gaussian noise and impulsive noise.[32] Adaptive median filters have also been proposed for removing impulse noise and preserving the image sharpness.[33] A fuzzy operator has been suggested for enhancement of blurred and noisy images.[34] A new approach to spatial adaptive image restoration, which employs minimum additional computational load compared to the direct techniques.[35] The use of wavelet transform presents a new method for adaptive restoration and yields very good edge preservation in the restored images. A novel algorithm for removing impulse noise from images which the nature of filtering operation is conditioned on a state variable.[36] The key of the algorithm is a classifier that indicates the probability of impulse corruption by operating on the rank ordered differences within a sliding window. This technique significantly outperforms a number of well-known techniques in the presence of impulsive, Gaussian and mixed type of noise. A reliable and efficient computational algorithm for restoring blurred and noisy images has been proposed by Li and Santosa. [37]

By using inverse filtering technique blurred images can be restored. In a recent publication, Malladi and Sethian have suggested a unified approach for noise removal, image enhancement, and shape recovery, this approach relies on the level of set formulation of curves and surface motion, which leads to a class of PDE-based algorithm. Enhancement of medical images can be successfully achieved by this technique. [38] Several adaptive Least Mean Square (LMS) filters for noise suppression from image. [39]

The de-noising of Magnetic Resonance Images using wave atom shrinkage proved that this approach achieves a better SNR compared to wavelet and curve let shrinkages.[40] A NL-Denoising method for Rician noise reduction.[41, 42] A test bed for baseline correction and noise filtering methods is implemented and compared.[43] A nonparametric Neighborhood Statistics method is proposed for MRI Denoising.[44] An adaptive wavelet-based Magnetic Resonance images denoising algorithm using wavelet shrinkage and mixture model concept.[45] The method to improve image quality based on determining the critical pulse sequence parameters by timing constraints from all gradient, rather than a single gradient of the image.[46] A new filter to reduce random noise in multicomponent MR images by spatially averaging similar pixels and a local principal component analysis decomposition using information from all available image components to perform the denoising process.[47]

A new signal estimator based upon the technique of "noise cancellation" which is commonly used in signal processing is used to recover signals corrupted by additive noise in MRI.[48] An estimator using a priori information for devising a single dimensional noise cancellation for the variance of the thermal noise in magnetic resonance imaging (MRI) systems called ML estimator.[49] Non-Local Means (NLM) filtering method for reducing artifacts caused in MRI due to under sampling of k-space (to reduce scan time).[50] A de-noising strategy along similar lines, namely NL-Means, but one principles in nonparametric regression.[51, 52]

A maximum a posteriori estimation technique that operates directly on the diffusion weighted images and accounts for the biases introduced by Rician noise for filtering diffusion tensor magnetic resonance images.[53] A novel approach to evaluating reconstructions for low-SNR magnetic resonance (MR) images.[54] a filtering process based on anisotropic diffusion.[55] Rudin-Osher-Fatemi was the first one to observe that if we minimize the total variation (TV) norm of the image under some given conditions, we will get a nonlinear diffusion filter.[56] This idea gives a rigorous mathematical tool to introduce nonlinear diffusion filters and has been used as a regularization method for many applications where one needs to identify discontinuous function. Motivated by the TV-norm filter, many similar filters were used.[57, 58, 59] A spatially adaptive TV model has been applied to partially parallel MRI (PP-MRI) image reconstructed using GRAPPA (Generalized approach to parallel magnetic resonance imaging) and SENSE (Sensitivity encoding MRI imaging.[60] The novel filtering method known as trilateral filtering (TF) works similar as Bilateral Filtering and tasks the geometric, photometric and local structural similarities to smooth the MR images.[61, 62]

A multitude of variation methods based on partial differential equations (PDE) have been developed for a wide variety of images and applications introduced in [63, 64] with some of these having applications to MRI.[65, 66, 67]

A noise removal technique using 4^{th} order PDE applied to MRI images.[68] However, such methods impose certain kinds of models on local image structure that are often too simple to capture the complexity of anatomical MR images. These methods, typically, do not take into account the bias introduced by Rician noise. Furthermore, such methods usually involve manual tuning of critical free parameters that control the conditions under which the models prefer one sort of structure over another; this has been an impediment to the widespread adoption of these techniques. A phase error estimation scheme based on iteratively applying a series of non-linear filters each used to modify the estimate into greater agreement with one piece of knowledge, until the output converges to a stable estimate. [69] A wavelet based multi scale products thresholding scheme using Dyadic Wavelet Transform for detecting Multi scale Edge for noise suppression of magnetic resonance images.[70]

Another class of methods relies on statistical inference on multi scale representation of images. A prominent example includes methods based on wavelet transforms. Healy was among the first to apply soft-thresholding based wavelet techniques for denoising MR images.[71] Hilton applies a threshold-based scheme for functional-MRI data[72] Nowak introduced the square magnitude MR image, includes a Rician noise model in the threshold-based wavelet denoising scheme and thereby corrects for the bias introduced by the noise.[73]

Pizurica rely on the prior knowledge of the correlation of wavelet coefficients that represent significant features across scales. [74] They first detect the wavelet coefficients that correspond to these significant features and then empirically estimate the PDFs of wavelet coefficients conditioned on the significant features. They employ these probabilities in a Bayesian denoising scheme. Robbins employed the empirical-Bayes approach to first obtain a maximum likelihood (ML) estimate of the prior distribution using the observations corrupted by a known noise, and then employ the estimated prior model to compute the posterior. [75]

Weismann address optimal image denoising using Markov statistics and empirical-Bayes approach.[76] Their discrete universal denoiser (DUDE) focuses on discrete signal intensities and subse-quently relies on inverting the channel transition matrix (noise model) to give a close-form estimate for source statistics from the observed statistics. Snyder also uses kernel density estimators for density deconvolution.[77] Black studied the relation between anisotropic diffusion and robust statistics. They implemented a robust estimation procedure that estimated a piecewise a smooth image from a noisy input image and demonstrated improved automatic stopping of the diffusion process with preservation of sharp bound-aries and better continuity of edges compared to the Perna-Malik method. Their rationale for applying robust statistics to anisotropic diffusion was from the case of piecewise constant images but was not extended to more general ones, like MRI, where there can be regions with slowly varying signal intensities and un sharp tissue boundary zones due to partial volume effects.[78]

Another approach to image restoration is nonparametric statistical methods. For instance propose an unsupervised information-theoretic adaptive filter, namely UINTA that relies on nonparametric MRF models derived from the corrupted images. [79, 80] UINTA restores images by generalizing the mean-shift procedure to incorporate neighborhood information. They show that entropy measures on first-order image statistics are ineffective for de-noising and hence, advocate the use of higher-order/Markov statistics. [81, 82] UINTA however, does not assume a specific noise model during restoration.

CHAPTER THREE

LITERATURE REVIEW

3.1: In 4 April **2014,** P.G.scholar & Vanitha.S, **"Denoising MRI Images Using A Non-Linear Digital Filter"**. Magnetic Resonance Imaging is the best technique used in medical fields for diagnosis of the diseases to treatment. Removing noise from the original MRI is still a challenging problem for researchers. Various approaches are designed and followed for Denoising. A new signal-preserving technique for noise suppression in event-related magnetic resonance imaging (MRI) data is proposed based on spectral subtraction. Simple form, the new method does not change the statistical characteristics of the signal or cause correlated noise. [83]

3.2: In 5 May **2014,** Monika Raghav & Sahil Raheja **"IMAGE DENOISING TECHNIQUES"**. In various fields and applications use of images are becoming increasingly popular like in field of medical, education etc. But the problem is that noise will be inevitably introduced in the image during image acquisition process. Another problem that a rises after denoising process is the destruction of the image edge structures and introduction of artifacts. For this there are several techniques proposed by other authors for image denoising as well as for edge preservation. In many papers, the aim to provide a review of some of those techniques that can be used in image processing (denoising). That paper outlines the brief description of noise, types of noise, image denoising and then the review of different techniques and their approaches to remove that noise. The aim of many review papers are to provide some brief and useful knowledge of denoising techniques for applications using images to provide an ease of selecting the optimal technique according to their needs. [84]

3.3: In **2013** Hagawa, R.; Kaneko, S.; Takauji, H., "**Using Extended Threevalued Increment Sign for a denoising model of high-frequency artifacts in JPEG images by estimation of specific frequency**" "Using Extended Three-valued Increment Sign for a denoising model of high-frequency artifacts in JPEG images by estimation of specific frequency,". Author presented a robust denoising model for high-frequency artifacts resulted by compressing images into JPEG. In this model, the authors used only simple evaluation value named Extended Three-valued Increment Sign (ETIS). ETIS represents the relationship of adjacent pixels, which one is brighter or almost the same. The authors expected that ETIS difference between Compressed Image and Noise Image would be small except edge region. Then they figured out the sum of the squares of those differences and utilized it in noise estimation. Only quantization process cause the artifacts, then they optimized DCT coefficient matrix in non-linearly based on ETIS, and estimated high-frequency artifacts as an independent approach without smoothing process. In the result, the model succeeded to reject noise with preservation of edge information. In addition, they compared the results with others those applied the traditional method called ε-filter and made sure that their method had similar or better improvement. [85]

3.4: In **2013** Jin Xu; Wei Wang; Jinghuai Gao; Wenchao Chen, **"Monochromatic Noise Removal via Sparsity-Enabled Signal Decomposition Method"**. "Monochromatic Noise Removal via Sparsity-Enabled Signal Decomposition Method," Monochromatic noise always interferes with the interpretation of the seismic signals and degrades the quality of subsurface images obtained by further processes. Conventional methods suffer from several problems in detecting the monochromatic noise automatically, preserving seismic signals, etc. In this letter, we present an algorithm that can remove all major monochromatic noises from the seismic traces in a relatively harmless way. Our separation model is set up upon the assumption that input seismic data are composed of useful seismic signals and single-frequency interferences. Based on their diverse morphologies, two waveform dictionaries are chosen to represent each component sparsely, and the separation process is promoted by the sparsity of both components in their corresponding representing dictionaries. Both synthetic and field-shot data are employed to illustrate the effectiveness of our method. [86]

3.5: In **2013** Padmagireeshan, S.J.; Johnson, R.C.; Balakrishnan, A.A.; Paul, V.; Pillai, A.V.; Raheem, A.A., **"Performance Analysis of Magnetic Resonance Image Denoising Using Contourlet Transform"** "Performance Analysis of Magnetic Resonance Image Denoising Using Contourlet Transform,". A medical image denoising algorithm using contourlet transform is proposed and the performance of the proposed method is analysed with the existing methods. Noise in magnetic resonance imaging has a Rician distribution and unlike AWGN noise, Rician noise is signal dependent. Separating signal from Rician noise is a tedious task. The proposed approaches were compared with other transform methods such as wavelet thresholding and block DCT. Hard, soft and semi-soft thresholding techniques are described and applied to test images with threshold estimators like universal threshold. The results are compared based on the parameters: PSNR and MSE. Numerical results show that the contour let transform can obtained higher PSNR than wavelet based and block DCT based denoising algorithms. [87]

3.6: In **2013** Fedak, V.; Nakonechny, A., **"Image de-noising based on optimized NLM algorithm"** Image denoising based on optimized NLM algorithm". Images and video are often coded using block based discrete cosine transform (DCT) or discrete wavelet transforms (DWT) that cause a great deal of visual distortions. Non- Local Means (NLM) algorithm is chosen by means of comparing complexity and quality of different algorithms and is considered to be the better algorithm for artifacts reduction. Besides, implementation of this algorithm is computationally intensive. In this note, improvements to the non-local means introduced are presented and very effective performance optimization approach is presented. This approach is based on additional memory usage for caching pixels distance in the image. We present the underlying framework and experimental results for video that is processed by NLM with different parameters. [88]

3.7: In **2011**, M. N. Nobi and M. A. Yousuf **"A New Method to Remove Noise in Magnetic Resonance and Ultrasound Images"**. It describe approximate digital implementations of two new mathematical transforms, explicitly, the ridgelet transform and the curvelet transform.These implementations suggest exact renovation, stability against noise, ease of implementation, and low computational complexity. A vital tool is Fourier-domain computation of an approximate digital Radon transform. This introduce a very simple interpolation in Fourier space which takes Cartesian samples and yields samples on a recto polar lattice, which is a pseudo-polar sampling set based on a concentric squares geometry. Regardless of the crudeness of interpolation, the visual performance is surprisingly good. Ridgelet transform applies to the Radon transform a special over complete wavelet pyramid whose wavelets have dense support in the frequency domain. Curvelet transform uses ridgelet transform as a component pace, and implements curvelet subbands using a filter bank of wavelet filters. In the tests reported here, simple thresholding of the curvelet coefficients is very competitive with "state of the art" techniques based on wavelets, counting thresholding of decimated or undecimated wavelet transforms and also with tree-based Bayesian posterior mean methods. Moreover, the curvelet reconstructions reveal higher perceptual excellence than wavelet-based reconstructions, presents visually sharper images and, in particular, higher quality revival of edges and of faint linear and curvilinear features. Existing presumption for curvelet and ridgelet transforms suggests that these new approaches can smash wavelet methods in certain image reconstruction problems. [89]

3.8: In **2009** Zuofeng Zhou, Jianzhong Cao, Weihua Liu **"Contourlet-based image denoising algorithm using adaptive windows"** Contourlet is new effective signal representation tool in many image applications. In this paper, a contourlet-based image-denoising algorithm using adaptive windows which utilizes both the captured directional information by the contourlet transform and the intrinsic geometric structure information of the image is proposed. The adaptive window in each of the contourlet sub band is first fixed by autocorrelation function of contourlet coefficients' energy distribution, and then the local Wiener filtering is used to denoise the noisy image. Experiments show that the proposed algorithm achieves better performance than current subsampled contourlet based image denoising algorithms. [90]

3.9: In **2007, "Regression Models for Identifying Noise Sources in Magnetic Resonance Images".** In medical image processing, medical images are corrupted by diverse type of noises. It is very important to attain accurate images to facilitate precise observations for the application. Removal of noise from medical images is a very exigent issue in the field of medical image processing. Most well recognized noise reduction methods, which are usually based on the local data of a medical image, are not resourceful for medical image noise reduction. This paper presents a proficient and simple method for noise reduction from medical images. In the future method, median filter is modified by adding more features. Experimental consequences are also compared with the other image filtering techniques. The quality of the output images is measured by the statistical quantity measures: peak signal-to-noise ratio (PSNR), signal-to-noise ratio (SNR) and root mean square error (RMSE). Experimental results of magnetic resonance (MR) image and ultrasound image demonstrate that the proposed algorithm is comparable to popular image smoothing algorithms. [91]

3.10: "MRI Brain Image Enhancement Using Filtering Techniques" Magnetic Resonance Image is one of the preeminent technologies currently being used for diagnosing brain cancer at early stages. This paper proposes a novel approach for the MRI image enrichment, which is based on the Modified Tracking Algorithm, Histogram Equalization and Center Weighted Median (CWM) filter. Two approaches introduced are: The first approach is applying the adapted tracking algorithm to eradicate the film perturbations, labels and skull region and then applying the Histogram Equalization and Center Weighted Median (CWM) filter techniques independently to enhance the images. [92]

CHAPTER FOUR

STUDY OF MR IMAGE DENOISING FILTERS

4.1 Introduction

Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the image. In this chapter describes of different methodologies for noise reduction or denoising giving an insight as to which algorithm should be used to find the most reliable estimate of the original image data given its degraded version. There are two basic approaches to image denoising, spatial filtering methods and transform domain filtering methods.

Filters play a major role in the image restoration process. The basic concept behind image restoration using linear filters is digital convolution and moving window principle. [93] Let $w\ (x)$ is the input signal subjected to filtering, and $z\ (x)$ be the filtered output. If the filter satisfies certain conditions such as linearity and shift invariance, then the output filter can be expressed mathematically in simple form as: [93]

$$Z\ (x) = \int w\ (t)\ h\ (x - t)\ dt \qquad (4\text{-}1)$$

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

$$Z = w * h \qquad (4\text{-}2)$$

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

$$Z\ (i) = \sum_{-\infty}^{+\infty} w\ (t)\ h\ (i - t) \qquad (4\text{-}3)$$

Although the limits on the summation in Equation (4-3) are ∞, the function $h\ (t)$ is usually zero outside some range. If the range over which $h\ (t)$ is non-zero is $(-k,\ +k)$, then the above Equation (4-3) can be written as

$$Z\ (i) = \sum_{i-k}^{i+k} w\ (t)\ h\ (i - t) \qquad (4\text{-}4)$$

This means that the output Z (*i*) at point *i* is given by a weighted sum of input pixels surrounding *i* where the weights are given by *h* (*t*).

4.1.1 Spatial filtering

A traditional way to remove noise from image data is to employ spatial filters. Spatial filters can be further classified into non-linear and linear filters.

I. Non-Linear Filters

With non-linear filters, the noise is removed without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum. Generally spatial filters remove noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in pictures invisible. In recent years, a variety of nonlinear median type filters such as weighted median,[94] rank conditioned rank selection,[95] and relaxed median [96] have been developed to overcome this drawback.

II. Linear Filters

Linear filters too tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal dependent noise. A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error. Linear filters too tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal-dependent noise.

Median filter:

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

The Median filter is much better at preserving sharp edges than the Mean filter. These advantages aid Median filters in denoising uniform noise as well from an image.

The Median filter is performed by taking the magnitude of all of the vectors within a mask and sorted according to the magnitudes. The pixel with the median magnitude is then used to replace the pixel studied. The simple Median filter has an advantage over the Mean filter since median of the data is taken instead of the mean of an image. The median of a set is more robust with respect to the presence of noise. The operation of median filter can be expressed as:

$$F(x,y) = \text{median}_{(s,t)\in S_{xy}} \{g\,(s,t)\} \qquad (4\text{-}5)$$

Where S_{xy} represents the set of coordinates in a rectangular sub image window, centered at point (x,y), and median represents the median value of the window.

Hybrid Median filter:

Hybrid median filter is windowed filter of nonlinear class that easily removes impulse noise while preserving edges. In comparison with basic version of the median filter hybrid one has better corner preserving characteristics. The basic idea behind filter is for any elements of the signal (image) apply median technique several times varying window Shape and then take the median of the got median values. The hybrid median filter takes two medians: in an “X” and in a “X” centered on the pixel. The output is the median of these two medians and the original pixel value.

For hybrid median filter there is good idea to extend image symmetrically. In other words we are adding lines at the top and at the bottom of the image and add columns to the left and to the right of it. A hybrid median filter has the advantage of preserving corners and other features that are eliminated by the 3 x 3 and 5 x 5 median filters. With repeated application, the hybrid median filter does not excessively smooth image details (as do the conventional median filters), and typically provides superior visual quality in the filtered image. One advantage of the hybrid median filter is due to its adaptive nature which allows the filter to perform better than the standard median filter on fast-moving picture information of small spatial extent. [97]

Average filter (Mean filter):

A mean filter acts on an image by smoothing it; that is, it reduces the intensity variation between adjacent pixels. The mean filter is nothing, but a simple sliding window spatial filter that replaces the center value in the window with the average of all the neighboring pixel values including self. By doing this, it replaces pixels that are unrepresentative of their surroundings. It is implemented with a convolution mask, which provides a result that is a weighted sum of the values of a pixel and its neighbors. It is also called a linear filter. The mask or kernel is a square. 5×5 or 3x3 square kernel are used. If the coefficients of the mask sum up to one, then the average brightness of the image is not changed. If the coefficients sum to zero, the average brightness is lost, and it returns a dark image. The mean or average filter works on the shift-multiply-sum principle. [93]

The mean filter is used in applications where the noise in certain regions of the image needs to be removed. In other words, the mean filter is useful when only a part of the image needs to be processed.

A Mean filter is the optimal linear filter which uses a mask over each pixel in the signal. Each of the components of the pixels which fall under the mask are averaged together to form a single pixel. [98]

The operation of Mean filter can be expressed as:

$$F(x,y) = \frac{1}{NM} \sum f(s,t) \in S_{xy}\, g(s,t) \qquad (4\text{-}6)$$

Where f is the restored image and g is the corrupted image.

Gaussian filter:

Gaussian filtering is used to remove noise and detail. It is not particularly effective at removing salt and pepper noise. Gaussian filtering is more effective at smoothing images. It has its basis in the human visual perception system. It has been found that neurons create a similar filter when processing visual images.

Gaussian filtering is used to blur images and remove noise and detail. In one dimension, the Gaussian function is:

$$G(x) = \frac{1}{\sqrt{2\Pi\sigma^2}}\, e^{-x^2/2\sigma^2} \qquad (4\text{-}7)$$

The Gaussian filter works by using the 2D distribution as a point-spread function; this is achieved by convolving the 2D Gaussian distribution function with the image. In this sense it is similar to the mean filter, but it used a different kernel that represents the shape of Gaussian hump. In 2D, the Gaussian distribution follows the equation:

$$F(x,y) = \frac{1}{2\Pi\sigma^2} \text{Exp} \frac{[x^2+y^2]}{2\sigma^2} \qquad (4\text{-}8)$$

Where σ is the standard deviation, once a suitable mask has been calculated, then the Gaussian smoothing can be performed using standard convolution. [99]

We need to produce a discrete approximation to the Gaussian function. This theoretically requires an infinitely large convolution kernel, as the Gaussian distribution is non-zero everywhere.

Fortunately the distribution has approached very close to zero at about three standard deviations from the mean. 99% of the distribution falls within 3 standard deviations. This means we can normally limit the kernel size to contain only values within three standard deviations of the mean.

Non Local mean:

The NLM filter was introduced by Buades in 2005. [100] this method of image denoising relies on the weighted average of all pixel intensities where the family of weights depends on the similarity between the pixels and the neighborhood of the pixel being processed.

The approach of Non-local means filter was introduced by Buades in 2005 [101] based on non-local averaging of all pixels in the image. The method was based on denoising an image corrupted by white gaussian noise with zero mean and variance. The approach of Non Local Means filtering is based on estimating each pixel intensity from the information provided from the entire image and hence it exploits the redundancy caused due to the presence of similar patterns and features in the image. In this method, the restored gray value of each pixel is obtained by the weighted average of the gray values of all pixels in the image. The weight assigned is proportional to the similarity between the local neighborhood of the pixel under consideration and the neighborhood corresponding to other pixels in the image.

Given a discrete noisy image v= {v (i)} for a pixel I the estimated value of NL[v] (*i*) is computed as weighted average of all the pixels i.e.:

$$NL[v]\ (i) = \sum_{j\epsilon i} w\ (i,j).v(j) \qquad (4\text{-}9)$$

Where the family of weights {w (i, j)} j depend on the similarity between the pixels *i* and *j*.

The similarity between two pixels *i* and *j* depends on the similarity of the intensity gray level vectors $v\ (Ni)$ and $v\ (N_j)$, where N_k denotes a square neighborhood of fixed size and centered at a pixel *k*. The similarity is measured as a decreasing function of the weighted Euclidea distance, $||v(N_i)-v(N_j)\ ||^2_{2,a}$, where a > 0 is the standard deviation of the Gaussian kernel.

The pixels with a similar grey level neighborhood to $v\ (Ni)$ have larger weights in the average. These weights are defined as,

$$W\ (i,j) = \frac{1}{Z\ (i)}\ e^{-||v(N_i)-v(N_j)\ ||^2_{2,a}/h^2} \qquad (4\text{-}10)$$

Where Z (*i*) is the normalizing constant and the parameter h acts as a degree of filtering. It controls the decay of the exponential function and therefore the decay of the weights as a function of the Euclidean distances.

Total variation:

Total variation based filtering was introduced by Rudin, Osher, and Fatemi. [102] TV denoising is an effective filtering method for recovering piecewise-constant signals. Many algorithms have been proposed to implement total variation filtering. The one described in these notes is by Chambolle.[103] (Note: Chambolle described another algorithm in).[104] Although the algorithm can be derived in several different ways, the derivation presented here is based on descriptions given in.[105, 106] The derivation is based on the min-max property and the majorization-minimization procedure.

Total variation is often used for image filtering and restoration, however, to simplify the presentation of the TV filtering algorithm these notes concentrate on one-dimensional signal filtering only. In addition, the algorithm described here may converge slowly for some problems.[105, 106]

Lee filter:

The Lee filter, [107] developed by Jong-Sen Lee, is an adaptive filter which changes its characteristics according to the local statistics in the neighborhood of the current pixel. The Lee filter is able to smooth away noise in flat regions, but leaves the fine details (such as lines and textures) unchanged. The Lee filter is designed to eliminate speckle noise while preserving edges and point features in radar imagery. Based on a linear speckle noise model and the minimum mean square error (MMSE) design approach, the filter produces the enhanced data. It uses small window (3×3, 5×5 and 7×7). Within each window, the local mean and variances are estimated. The distinct characteristic of the filter is that in the areas of low signal activity (flat regions) the estimated pixel approaches the local mean, whereas in the areas of high signal activity (edge areas) the estimated pixel favors the corrupted image pixel, thus retaining the edge information. It is generally claimed that human vision is more sensitive to noise in a flat area than in an edge area. The major drawback of the filter is that it leaves noise in the vicinity of edges and lines. However, it is still desirable to reduce noise in the edge area without sacrificing the edge sharpness.

Bilateral filter:

Bilateral filter is a non-linear filter, which replaces the pixel value by an average of similar and nearby pixel, by taking the weighted sum of pixels in a local neighborhood. The weight depends on both the spatial distance and the intensity distance. In this way, it preserves the edges well while averages out the noises. When a bilateral filter is applied to a pixel at location x, the output is mathematically expressed as:

$$I^{o}(x) = \frac{1}{C} \sum \frac{e^{-\|y-x\|}}{2\sigma_{d}^{2}} \frac{e^{-\|I(y)-I(x)\|}}{2\sigma_{r}^{2}} \; I(y) \qquad (4\text{-}11)$$

Where σ_d and σ_r area parameters controlling the fall-off of weights in spatial and intensity domain, N(x) is a spatial neighborhood of pixel I(x), and C is the normalization constant and defined as:

$$C = \sum_{y \in N(x)} \frac{e^{-\|y-x\|^{2}}}{2\sigma_{d}^{2}} \frac{e^{-\|I(y)-I(x)\|^{2}}}{2\sigma_{r}^{2}} \; I(y) \qquad (4\text{-}12)$$

4.1.2 Transform Domain filtering

An example of the transform domain filtering methods is wavelet domain filter.

*Wavelet domain filter:

Wavelet transform, due to its localization property, has become an indispensable signal and image processing tool for a variety of applications, including compression and denoising. A wavelet is a mathematical function used to decompose a given function or continuous-time signal into different frequency components and study each component with a resolution that matches is scale. A wavelet transform is the representation of a function by wavelets. The wavelets are scaled and translated copies (known as daughter wavelets) of a finite length or fast decaying oscillating waveform (known as mother wavelet). Wavelet transforms are classified into continuous wavelet transform (CWT) and discrete wavelet transform (DWT).

Wavelets are mathematical functions that analyze data according to scale or resolution. [108] They aid in studying a signal in different windows or at different resolutions. For instance, if the signal is viewed in a large window, gross features can be noticed, but if viewed in a small window, only small features can be noticed.

Wavelets provide some advantages over Fourier transforms. For example, they do a good job in approximating signals with sharp spikes or signals having discontinuities. Wavelets can also model speech, music, video and non-stationary stochastic signals. Wavelets can be used in applications such as image compression, turbulence, human vision, radar, earthquake prediction, etc. [108]

Wavelet filtering exploits the decomposition of the image into the wavelet basis and zeroes out the wavelet coefficients to denoise the image. Wavelet analysis is particularly useful for the analysis of transient, no stationary, or time varying signals.

Wavelets can be used to analyze signals in different spatial resolutions. Their advantage is in their ability to analyze a signal with accuracy in both the time and frequency domains. [109]
This is not the case when applying traditional Fourier analysis, where there is significant accuracy in the frequency domain, but less accuracy in the temporal domain. In other words, increasing accuracy in one domain implies a decrease in precision in the other domain. Wavelets are also known for their capacity to identify singularities associated with fine variations of the signal to be evaluated. For denoising, we need to identify the specific image scales where most of the image energy lies.

Denoising filtering in the wavelet domain is based on the idea of the Daubechies Symlet wavelet and on soft-thresholding denoising. It was firstly proposed by Donoho and also further investigated by Zhong and Cherkassky. [109]
The Symlet family of wavelets, although not perfectly symmetrical, was designed to have the least asymmetry and the highest number of vanishing moments for a given compact support.

4.2 The Filters Method

Filters that explained previous (Median, Hybrid Median, Average (Mean), Gaussian, Non local Mean, Wavelet, Total variation, Lee and Bilateral) at the size is (3x3) and (5x5) applied to noise free MR image respectively.

4.2.1 The Filters Algorithm

Step 1: input image is noise free image.
Step 2: add Rician noise 5% & 12% to input image.
Step 3: apply filter.
Step 4: output image.

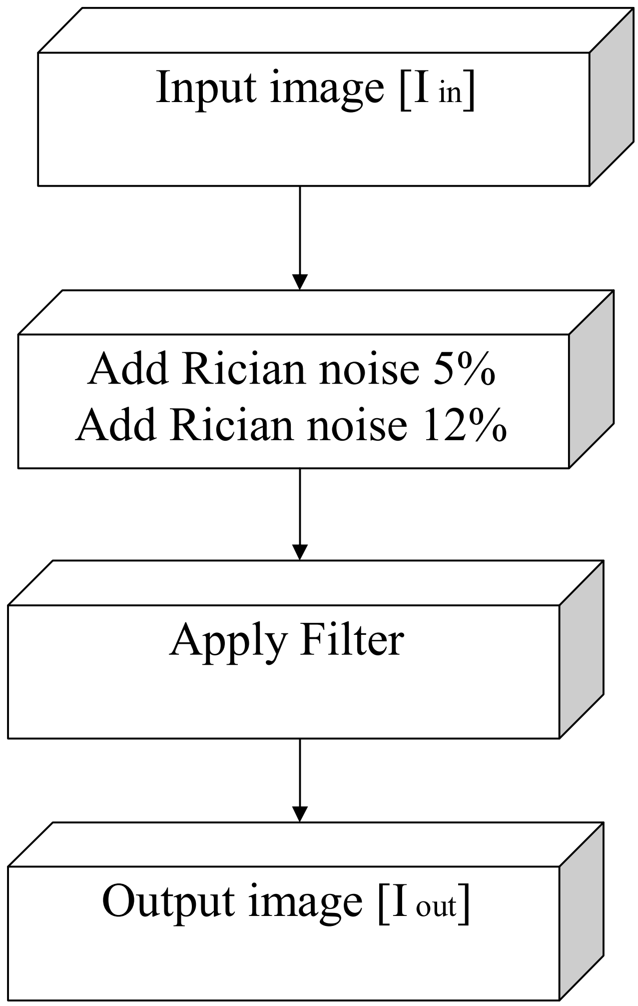

Figure 4.1: work flow. The input image was noise free image the rician noise added to it then denoised by different types of filters.

4.3 Experimental Results

The existing filters: Median, Hybrid Median, Average (Mean), Gaussian, Non local means, Wavelet, Total variation, Lee and Bilateral filters are simulated on MATLAB. The tested MR images are Brain and Ankle (from website). [110, 111]

For the performance evaluation of these filters, MR magnitude data has been generated by adding 5% Rician noise & 12% Rician noise free-images. Two types of images for MRI were used (Brain and Ankle MR Images); first to do the performance evaluation 5% Rician noise to original images was added. After the addition of noise, apply each filter that say previous for the reduction of noise. The visual performances of the filters are shown in Figure 4.2 to Figure 4.5.

Mean squared error (MSE), signal-to-noise ratio (SNR), university quality index (UQI) and method noise has been taken as performance measures. The MSE, SNR and UQI values of the different filters for various MR images are given in Table 4.1 and Table 4.2.

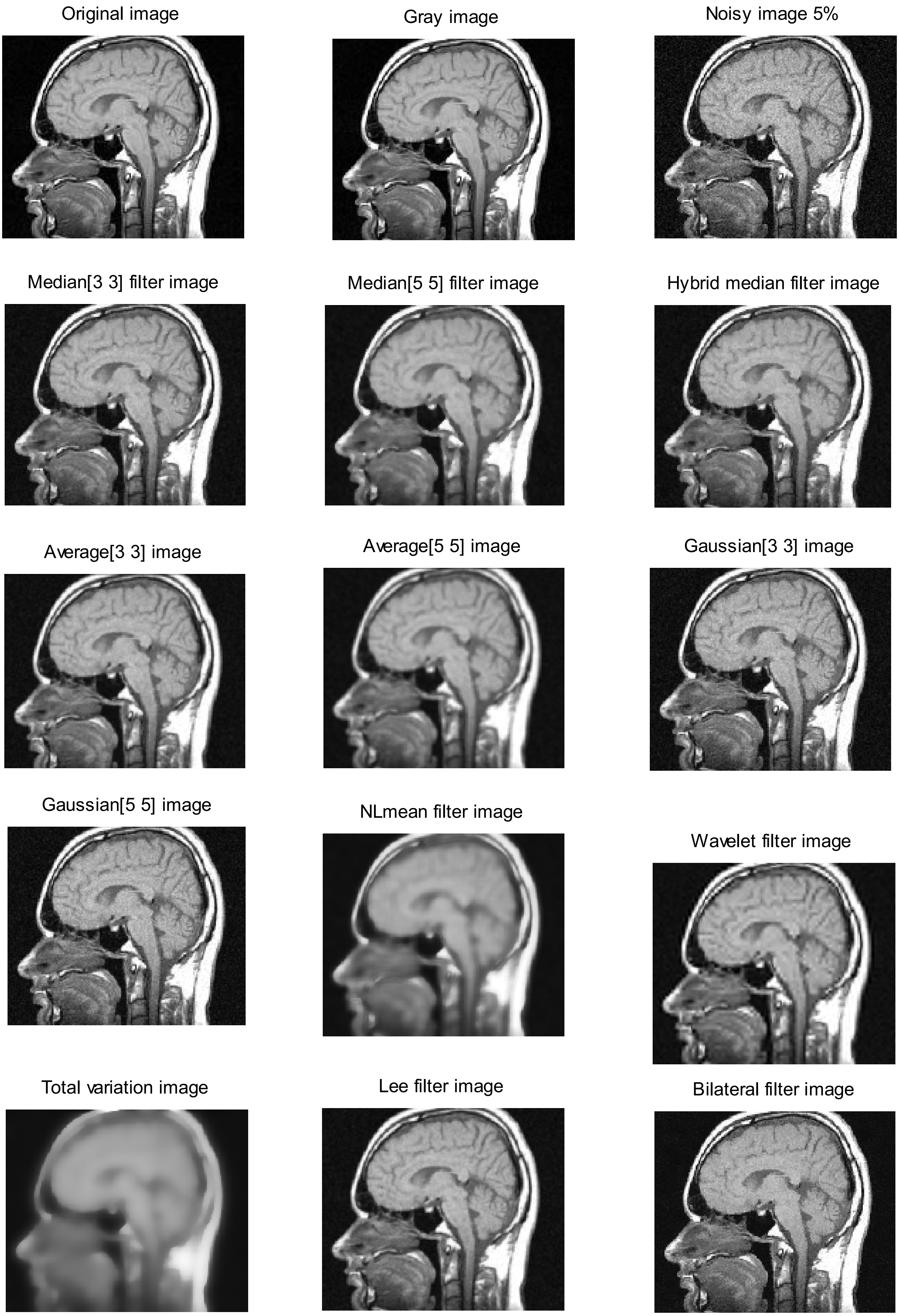
Original image
Gray image
Noisy image 5%
Median[3 3] filter image
Median[5 5] filter image
Hybrid median filter image
Average[3 3] image
Average[5 5] image
Gaussian[3 3] image
Gaussian[5 5] image
NLmean filter image
Wavelet filter image
Total variation image
Lee filter image
Bilateral filter image

Figure 4.2: Images filtering methods for Brain MR Image 5%

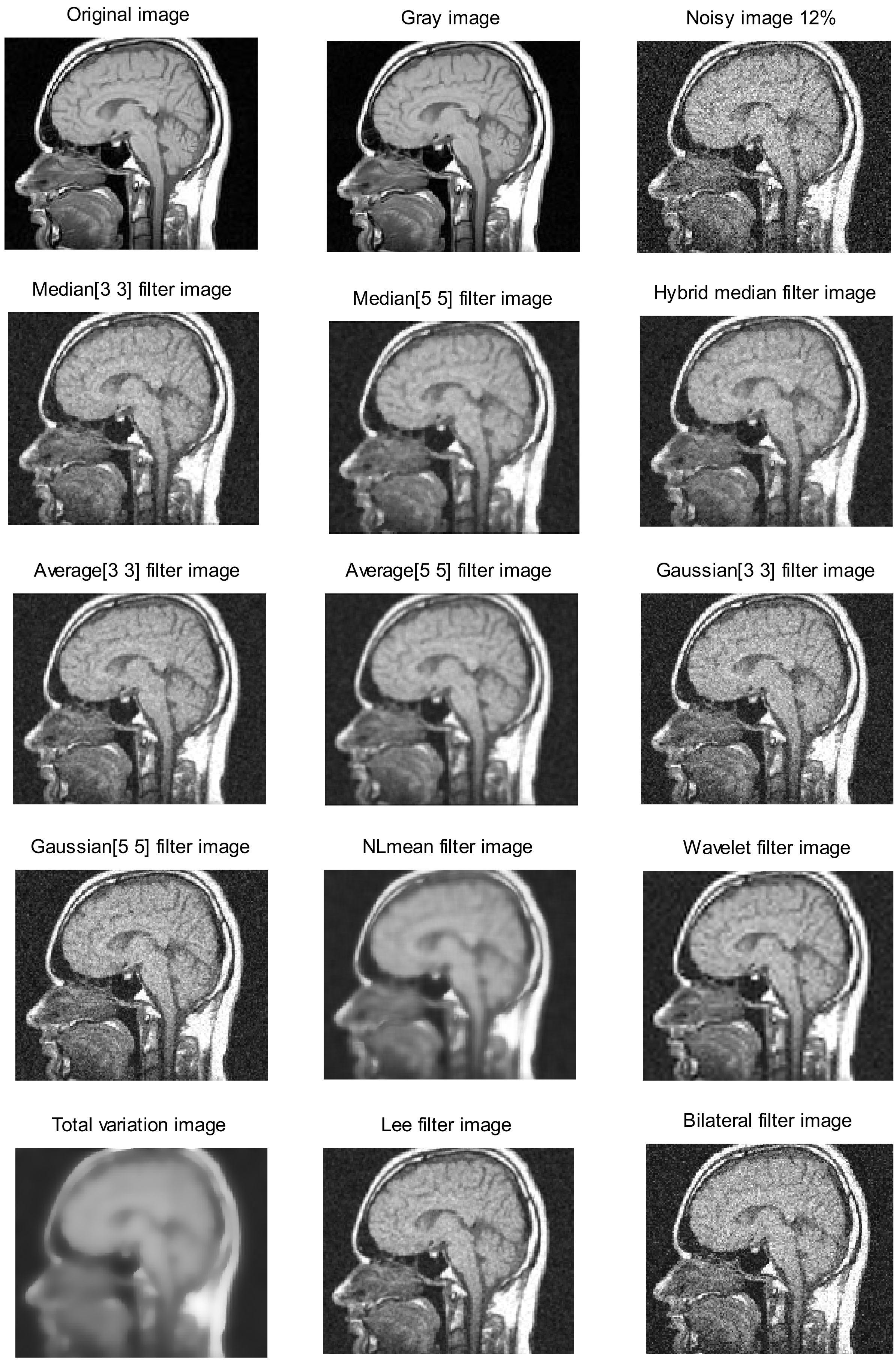

Figure 4.3: Images filtering methods for Brain MR Image 12%

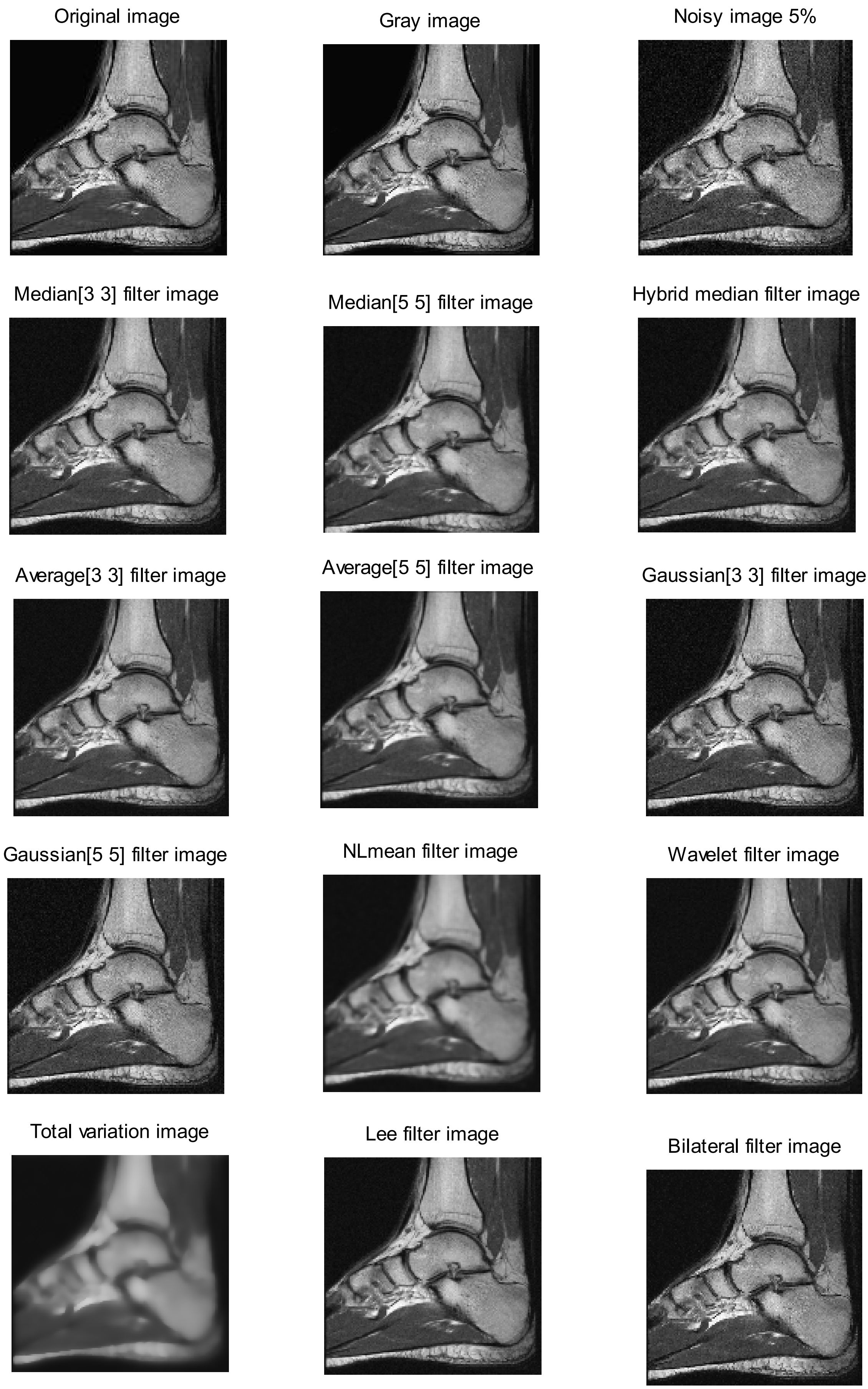

Figure 4.4: Images filtering methods for Ankle MR Image 5%

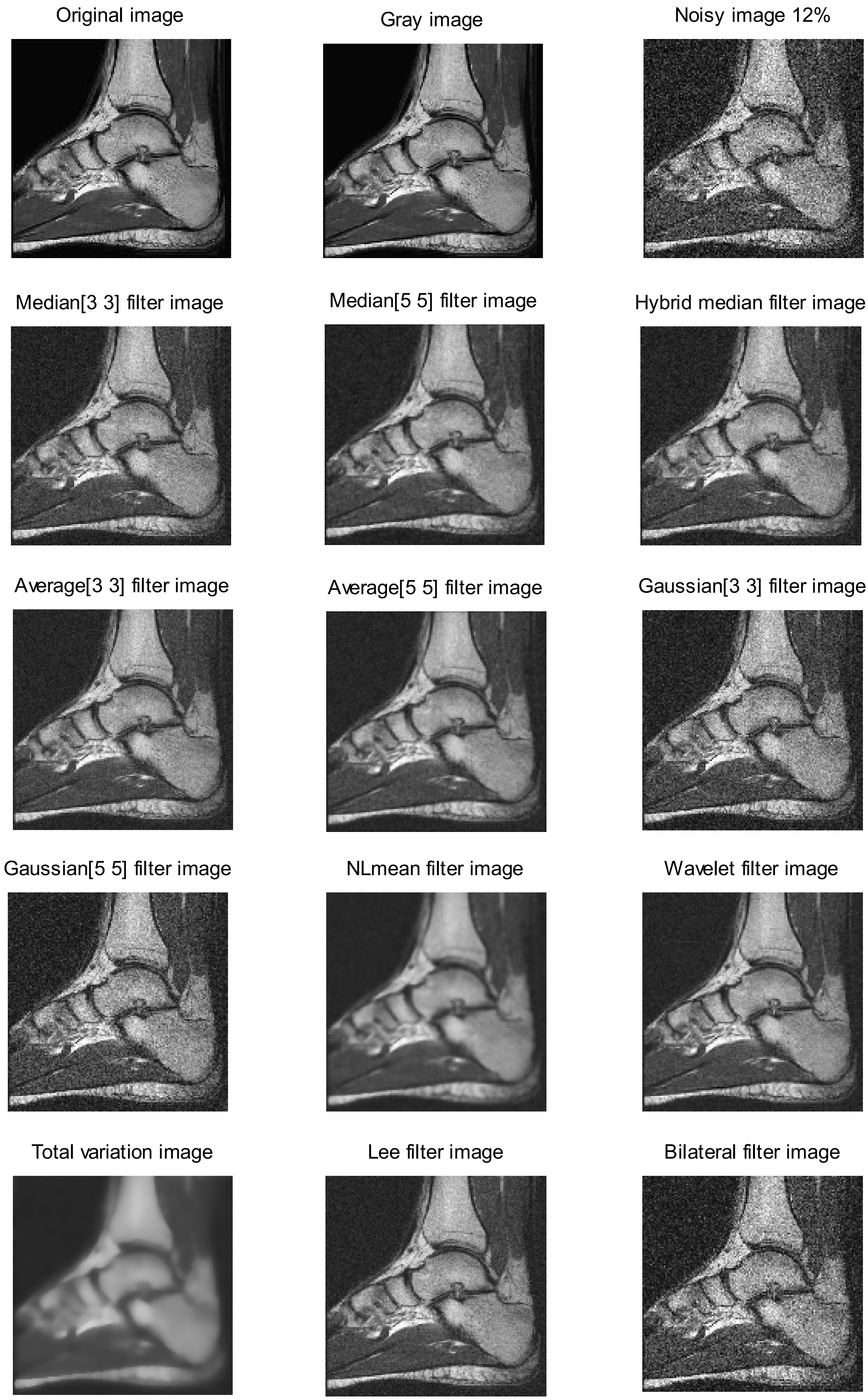

Figure 4.5: Images filtering methods for Ankle MR Image 12%

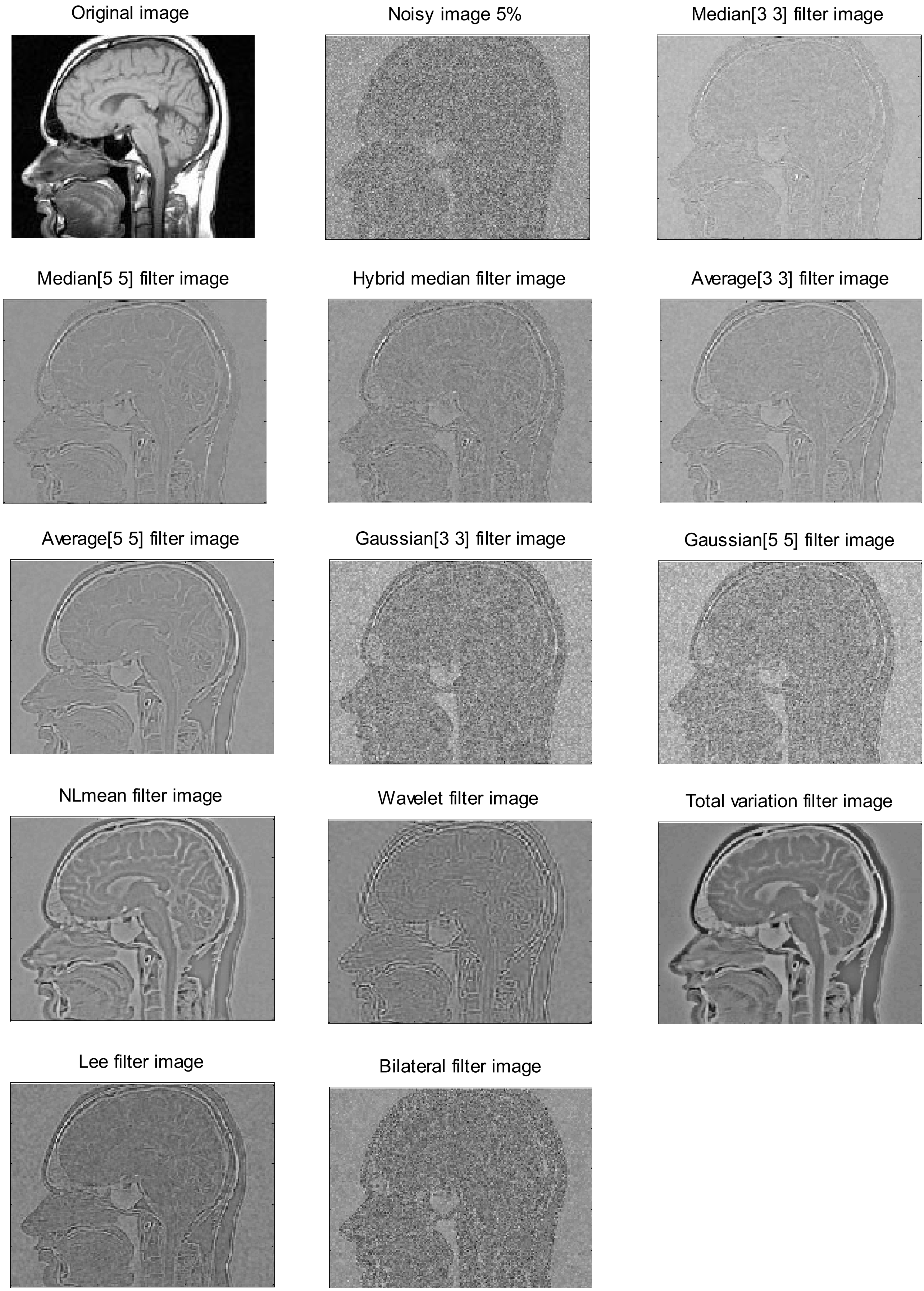

Figure 4.6: Images method noise for Brain MR Image 5%

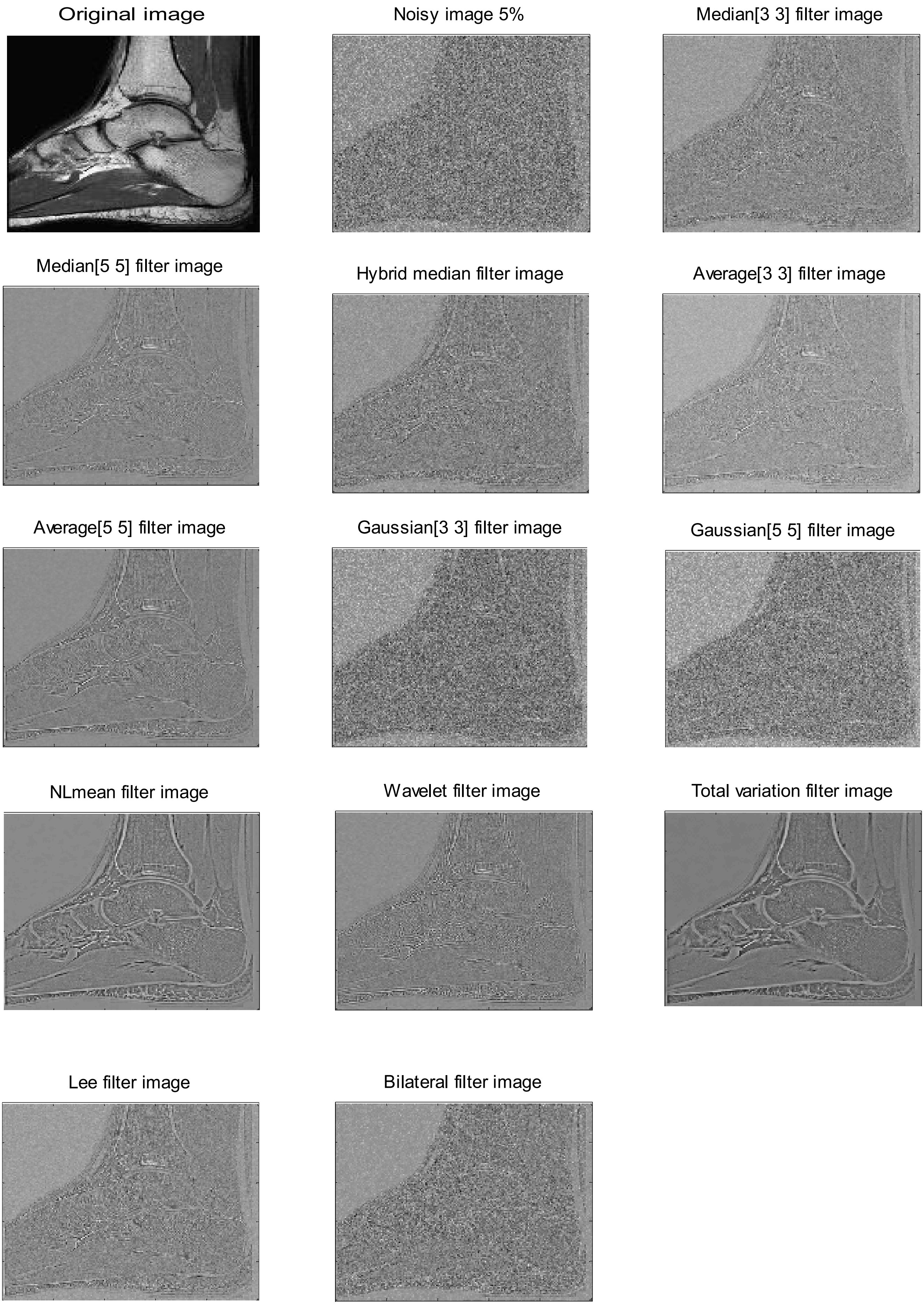
Original image
Noisy image 5%
Median[3 3] filter image
Median[5 5] filter image
Hybrid median filter image
Average[3 3] filter image
Average[5 5] filter image
Gaussian[3 3] filter image
Gaussian[5 5] filter image
NLmean filter image
Wavelet filter image
Total variation filter image
Lee filter image
Bilateral filter image

Figure 4.7: Images method noise for Ankle MR Image 5%

Table 4.1: The mean square error (MSE), the signal to noise ratio (SNR) and university quality index (UQI) for Brain MR image (5% & 12% Rician noise) denoised by filters.

Image	Brain MR image 5% 250x300			Brain MR image 12% 250x300		
Metrices	MSE	SNR	UQI	MSE	SNR	UQI
Median [3 3]	0.04	21.36	0.669	0.09	14.62	0.531
Median [5 5]	0.06	18.33	0.594	0.09	14.19	0.503
hybrid Median	0.04	20.87	0.65	0.09	14.21	0.503
Average [3 3]	0.05	20.27	0.683	0.09	14.39	0.553
Average [5 5]	0.07	16.43	0.566	0.1	13.3	0.499
Gaussian [3 3]	0.04	21.37	0.655	0.1	13.38	0.474
Gaussian [5 5]	0.04	21.34	0.655	0.1	13.37	0.475
NL Mean	0.09	14.78	0.362	0.12	12.27	0.337
Wavelet	0.06	17.77	0.585	0.1	13.38	0.499
Total Variation	0.13	11.29	0.195	0.15	9.92	0.179
Lee	0.04	20.47	0.681	0.09	14.34	0.558
Bilateral	0.04	20.93	0.626	0.12	11.96	0.399

Table 4.2: The mean square error (MSE), the signal to noise ratio (SNR) and university quality index (UQI) for Ankle MR image (5% & 12% Rician noise) denoised by filters.

Image	Ankle MR image 5% 500x500			Ankle MR image 12% 500x500		
Metrices	MSE	SNR	UQI	MSE	SNR	UQI
Median [3 3]	0.03	20.72	0.578	0.08	13.29	0.404
Median [5 5]	0.04	19.25	0.467	0.08	13.62	0.365
hybrid Median	0.04	20.34	0.559	0.08	13.07	0.377
Average [3 3]	0.03	20.68	0.599	0.08	13.29	0.438
Average [5 5]	0.05	18.4	0.465	0.08	13.14	0.379
Gaussian [3 3]	0.04	20.15	0.578	0.1	11.79	0.349
Gaussian [5 5]	0.04	20.17	0.58	0.1	11.81	0.35
NL Mean	0.06	15.96	0.269	0.1	12.3	0.237
Wavelet	0.04	18.57	0.478	0.08	13.04	0.379
Total Variation	0.08	14.4	0.158	0.11	10.91	0.133
Lee	0.03	20.77	0.603	0.08	13.26	0.439
Bilateral	0.04	19.73	0.542	0.11	10.42	0.273

4.4 Discussion

In the comparison we shall compare all filters that explain previous and this based on five well-defined criteria: MSE, SNR, UQI and the method noise. Note that every criterion measures a different aspect of denoising method. It is easy to show that only one criterion is not enough to judge the restored image and so one expects a good solution to have a high performance under the four criteria. Most filters are not bad and the Median (3X3), Median (5x5). Gaussian (3x3) and Gaussian (5x5) are good images result, but the Non Local Mean filter the result image is sharp, low noise and few artefacts. And the Total Variation filter the result image is low noise and low details.

4.4.1 Method noise comparison

In chapter two we explain the method noise that show us the geometric features or details are preserved by the denoising process and which are eliminated. In order to preserve as many features as possible of the original image, the method noise should look as much as possible like rician noise. Figure 4.6 and Figure 4.7 display the method noise of the different filters for two types of MR images.

4.4.2 Image metrics comparison

In Table 4.1 and Table 4.2 three statistical parameters were used to evaluate different denoising method MSE, SNR and UQI. Each parameter measures a specific means of these filters, as we explain in chapter two a smaller MSE indicates that the estimate is closer to the original image and the SNR is higher for a better-transformed image and lower for a poorly transformed image. It measures image fidelity, which is how closely the denoised image resembles the original image. The range of university quality index (UQI) is [-1, 1] and the bigger university quality index (UQI) value is the better the image performance, and the biggest value of (UQI) is equal 1.

From Table 4.1 it is observed that the filters: the Bilateral, Lee, Gaussian, Hybrid median, Median [3 3] filters are better in terms of MSE, and the Median [3 3], Gaussian filters are better in terms of SNR. The Lee, Average (Mean), Median [3 3] filters are better in terms of UQI.

CHPTER FIVE

PROPOSED TECHNIQUE

5.1 Introduction

This chapter explained the proposed technique that used to denoised MR image, this technique is a combination of wavelet decomposition and reconstructed by Bilateral filter and Lee filter.

Firstly, the wavelet transform has become an essential tool for many applications. However the wavelet transform has been presented a method representing a time frequency method. Continuous wavelets transform (CWT), and the wavelet transform generally has used for the decomposition of the signal into high and low frequency components. The wavelet coefficient represents a measure of similarity in the frequency content between a signal and a chosen wavelet function. These coefficients are computed as a convolution of the signal and the scaled wavelet function, which can be interpreted as a dilated band-pass filter. In practice, the wavelet transform is implemented with a perfect reconstruction filter bank using orthogonal wavelet family. The idea is to decompose the signal into sub-signals corresponding to different frequency contents. In the decomposition steps, a signal is decomposed on to a set of orthonormal wavelet function that constitutes a wavelet basis. The most common wavelets providing the orthogonally properties are Daubechies, Symlets, Coiflets and discrete Meyer in order to provide reconstruction using the fast algorithms.

The use of wavelet transform as filter bank called as DWT (Discrete Wavelet Transform). The DWT of a signal produces a non-redundant restoration, which provides better spatial and spectral localization of signal formation, compared with other multi-scale representation such as Gaussian and Laplacian pyramid. The result of the DWT is a multilevel decomposition, in which the signal is decomposed in ‘approximation’ and 'detail' coefficients at each level. This is made through a process that is equivalent to low-pass and high passes filtering, respectively.

If a signal x (t) decomposed into low and high frequency components that they are respectively named as approximation coefficients and detail coefficients, x (t) reconstructed as:

$$X(t) = \sum_{m=1}^{L} \left[\sum_{k=-\infty}^{\infty} D_m(k)\Psi_{m,k}(t) + \sum_{k=-\infty} A_l(k)\, \phi_{l,k}(t) \right] \qquad (5\text{-}1)$$

Where $\Psi_{m,k}$ (t) is discrete analysis wavelet, and $\phi_{1,k}(t)$ is discrete scaling, $D_m(k)$ is the detailed signal at scale2^m, and $A_l(k)$ is the approximated signal at scale2^m, $D_m(k)$ and $A_l(k)$ is obtained using the scaling and wavelet filters.

$$h(n) = 2^{-1/2[\phi(t),\ \phi(2t-n)]}$$

$$g(n) = 2^{-1/2[\Psi(t),\ \phi(2t-n)]} \qquad (5\text{-}2)$$

$$= (-1)^n\, h(1-n)$$

The wavelet coefficient can be computed by means of a pyramid transfer algorithm. The algorithms refer to a FIR filter bank with low-pass filter **h**, high-pass filter **g**, and down sampling by a factor 2 at each stage of the filter bank.

In 2D case, the image signal is considered as rows and columns as if they are one dimensional signal. In DWT, firstly the each rows of the image is filtered, then the each columns are filtered as in 1D case. The result of this process gives four images approximation (LL_i), horizontal details (LH_i), vertical details (HL_i) and diagonal details (HH_i) where i represent the level of decomposition. Because of sub sampling after each filtering, the result sub images of the original image have the quarter size of the original image. [112]

Secondly, as explained in chapter 3 the goal of Lee filter and Bilateral filter is to filter out noise that has corrupted an image.

5.2 The Proposed Technique Algorithm

Step 1: input image is noise free image.

Step 2: add Rician noise to the input image.

Step 3: apply Bilateral filter to get image [I_a] and Lee filter to get image [I_b].

Step 4: decompose image [I_a] into sub-bands LL_{ia} , LH_{ia} , HL_{ia} and HH_{ia}.

Step 5: decompose image [I_b] into sub-bands LL_{ib} , LH_{ib} , HL_{ib} and HH_{ib}.

Step 6: mixing the sub-bands LL_{ia} and LH_{ib} ,HL_{ib} , HH_{ib} .

5.3 Wavelet sub-bands

In the transform domain, the main features of the image correspond to low-frequency information while finer details and noise are associated to high frequencies. Nonetheless, noise is not a pure high-frequency component in most images. Noise is spanned over a certain range of frequencies in the image with mainly middle and high components.

In Lee filter, efficiently remove most of frequencies of noise but tend to spoil the main features of the image, whereas the Bilateral filter, tend to better preserve the image components but cannot completely remove all frequencies of noise. As a consequence, the following workflow is shown in figure 5.1

<u>Selection of Wavelet sub-bands:</u>

Once the original image [I_{in}] has been denoised using Bilateral filter and Lee filter, a 2D DWT at the first level is performed on both [I_a] and [I_b]

Images. For each image four sub-bands are obtained: LL_i, LH_i, HL_i and HH_i .

1. In the four wavelet sub-bands obtained with [I_b], the frequencies corresponding to noise are efficiently removed from the high frequencies whereas the low frequencies associated to the main features are spoiled.

2. In the four wavelet sub-bands obtained with [I_a], the low frequencies associated to main features are efficiently preserved whereas residual frequencies corresponding to noise are present in high frequencies.

Thus, the highest frequencies of I_b are filtered using Lee filter to ensure noise reduction completely, and then the highest frequencies of I_b (LH_{ib}, HL_{ib} and HH_{ib}) are mixed with the lowest frequencies of I_a (LL_{ia}) by inverse wavelet transform (idwt2) to obtain the output proposed technique image.

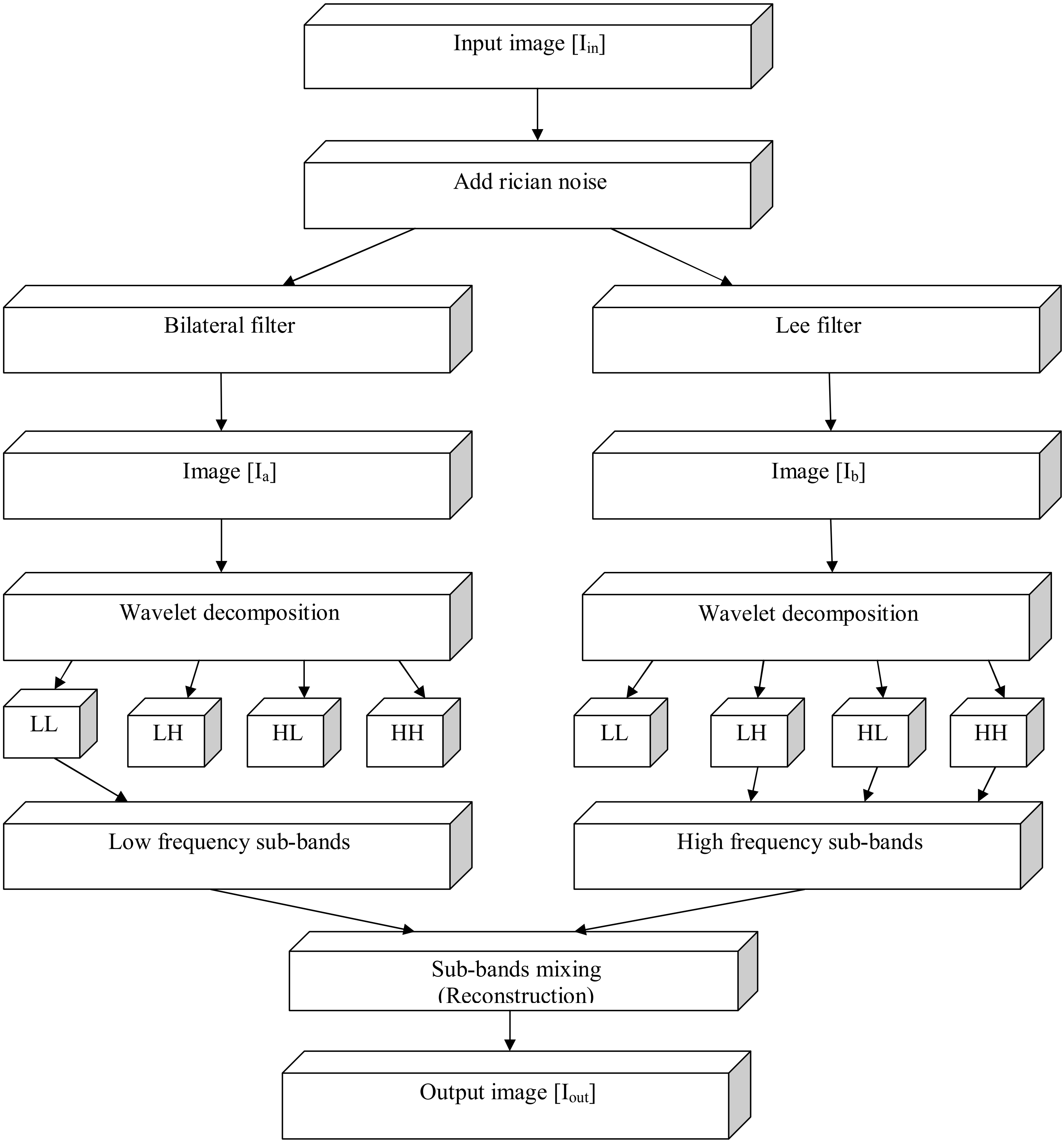

Figure 5.1: Workflow. First, the input image was noise free image the rician noise added to it, then denoised by Bilateral filter and Lee filter result tow images [I_a andI_b] then each image decomposed into low-and high-frequency sub-bands by dwt2, the high frequency sub-bansd of image I_b and the low frequency sub-bands of image I_a are mixed (reconstruction) the image by idwt2, to get output image.

5.4 Experimental Results

The proposed technique by Bilateral filter and Lee filter has been simulated on MATLAB The test MR images are Brain and Ankle (loaded from web). [110, 111]

These images are simulated by adding Rician noise at 5% and 12%, to noise free images. After addition the proposed algorithm is applied to reduction Rician noise.

The proposed technique has been applied to real MR images of adult humans (Brain and Ankle). The visual performance of the proposed technique and the different filtering techniques are explain in section one, at different noise levels for various synthetic and real MR images is shown in Figure 5.2 to Figure 5.6.

The images quality evaluation metrics values for the synthetic MR images are shown in Figure 5.7 to Figure 5.14.

Mean squared error (MSE), signal-to-noise ratio (SNR), the university quality index (UQI) and method noise was taken as performance measures. The MSE, SNR and UQI values of the proposed technique and different filtering techniques that explain in section one at different noise levels for various synthetic and real MR images are given in Table 5.1, Table 5.2.

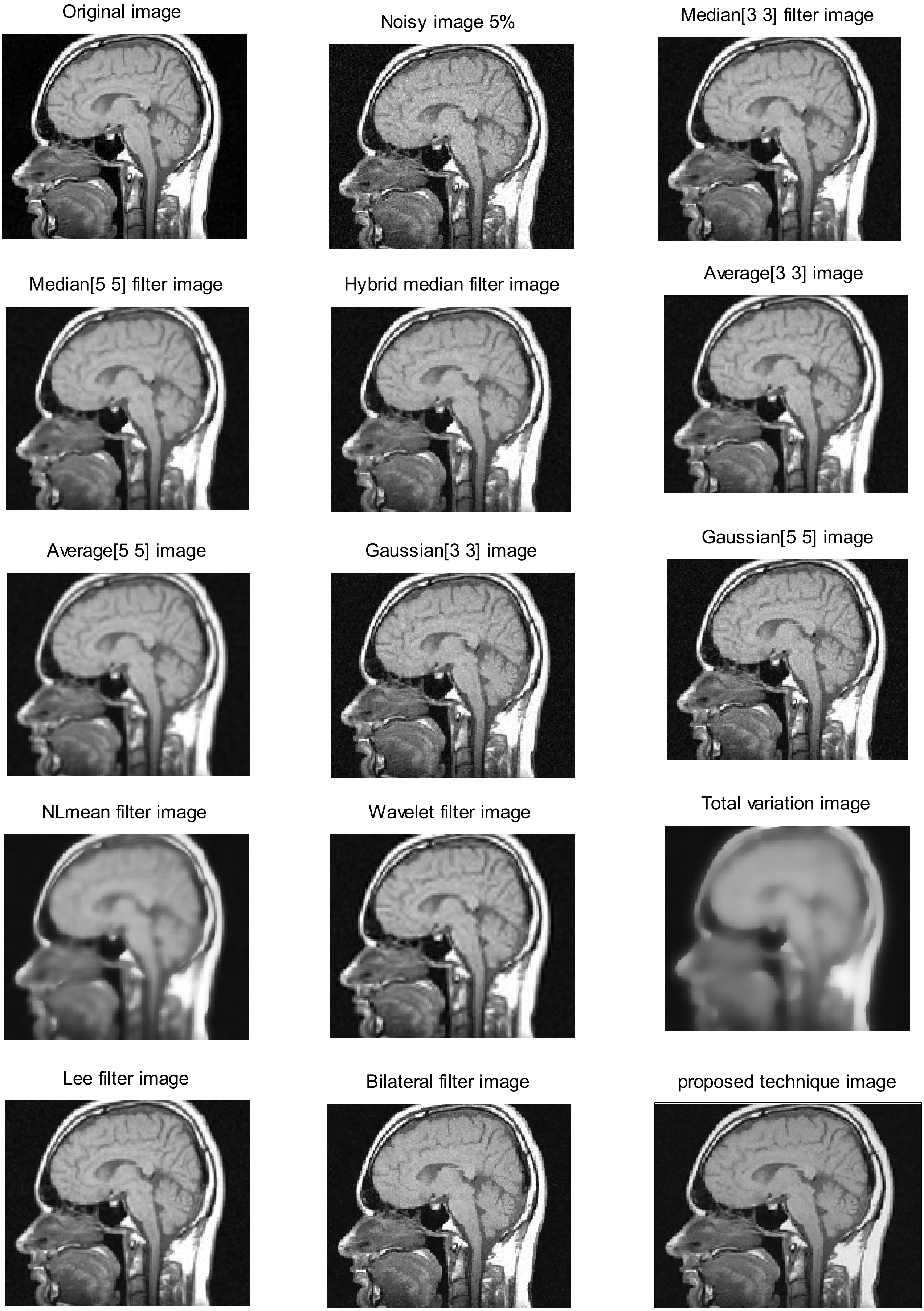

Figure 5.2: Images filtering methods for Brain MR Image 5%

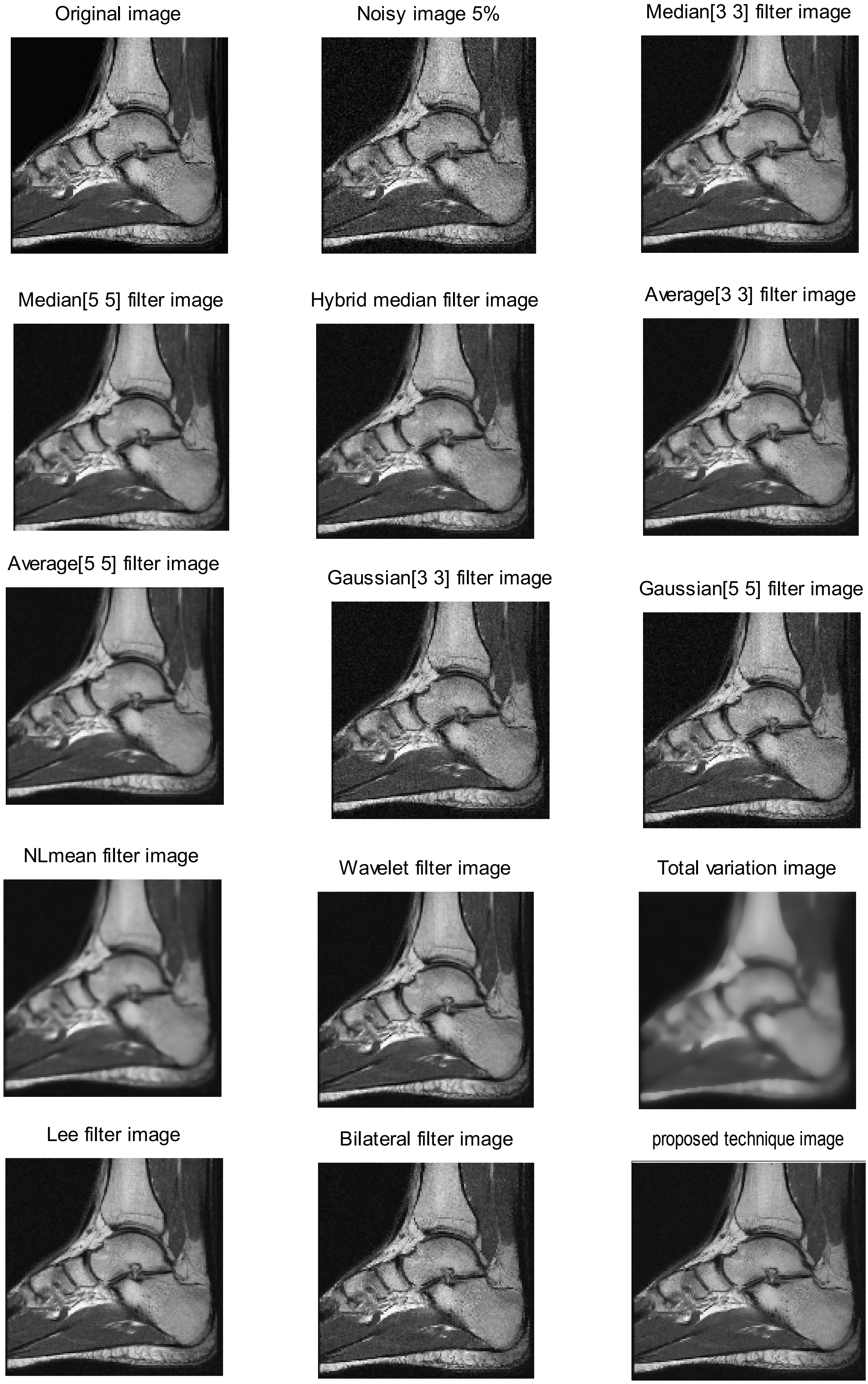

Figure 5.3: Images filtering methods for Ankle MR Image 5%

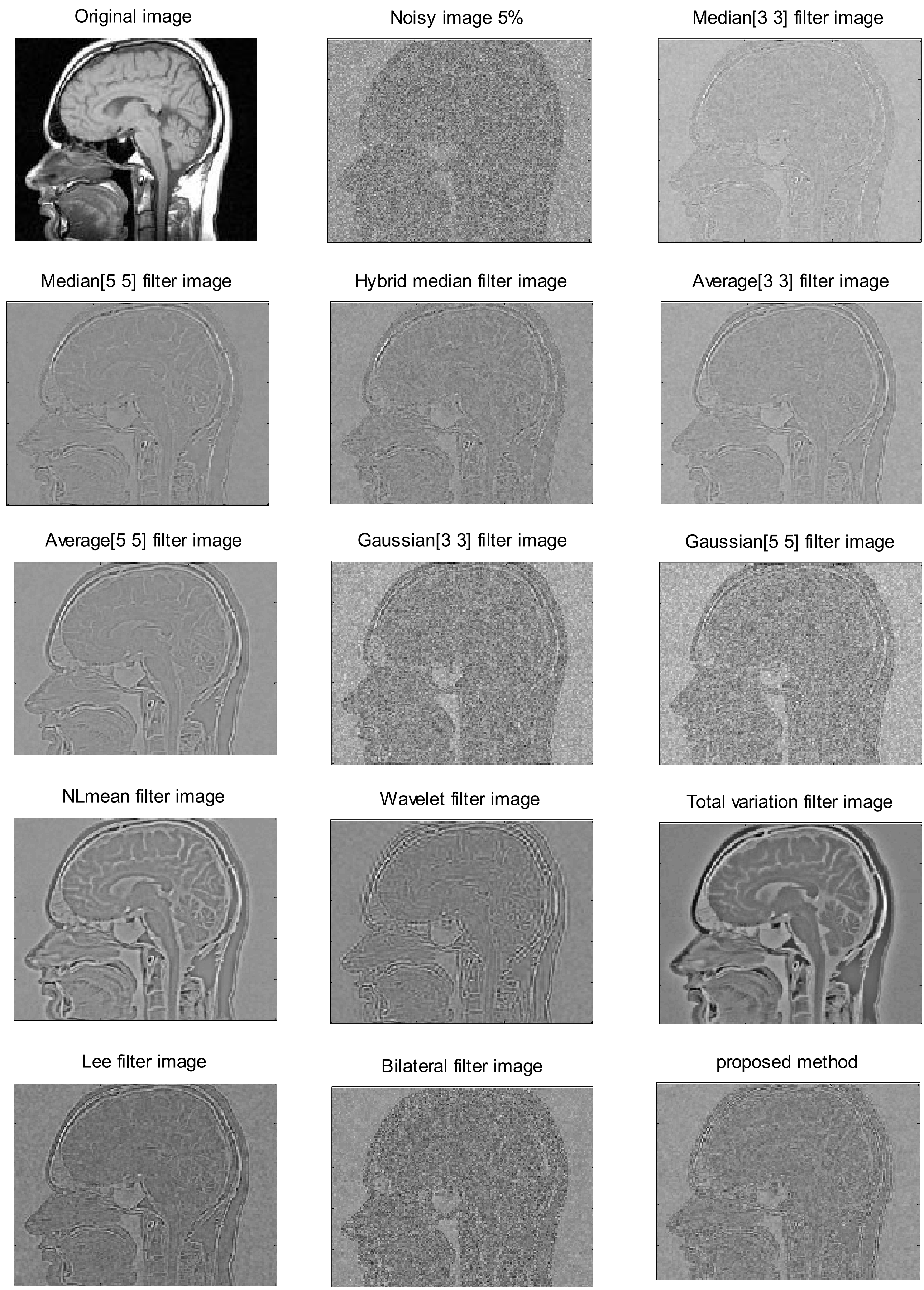

Figure 5.4: Images method noise for Brain MR Image 5%

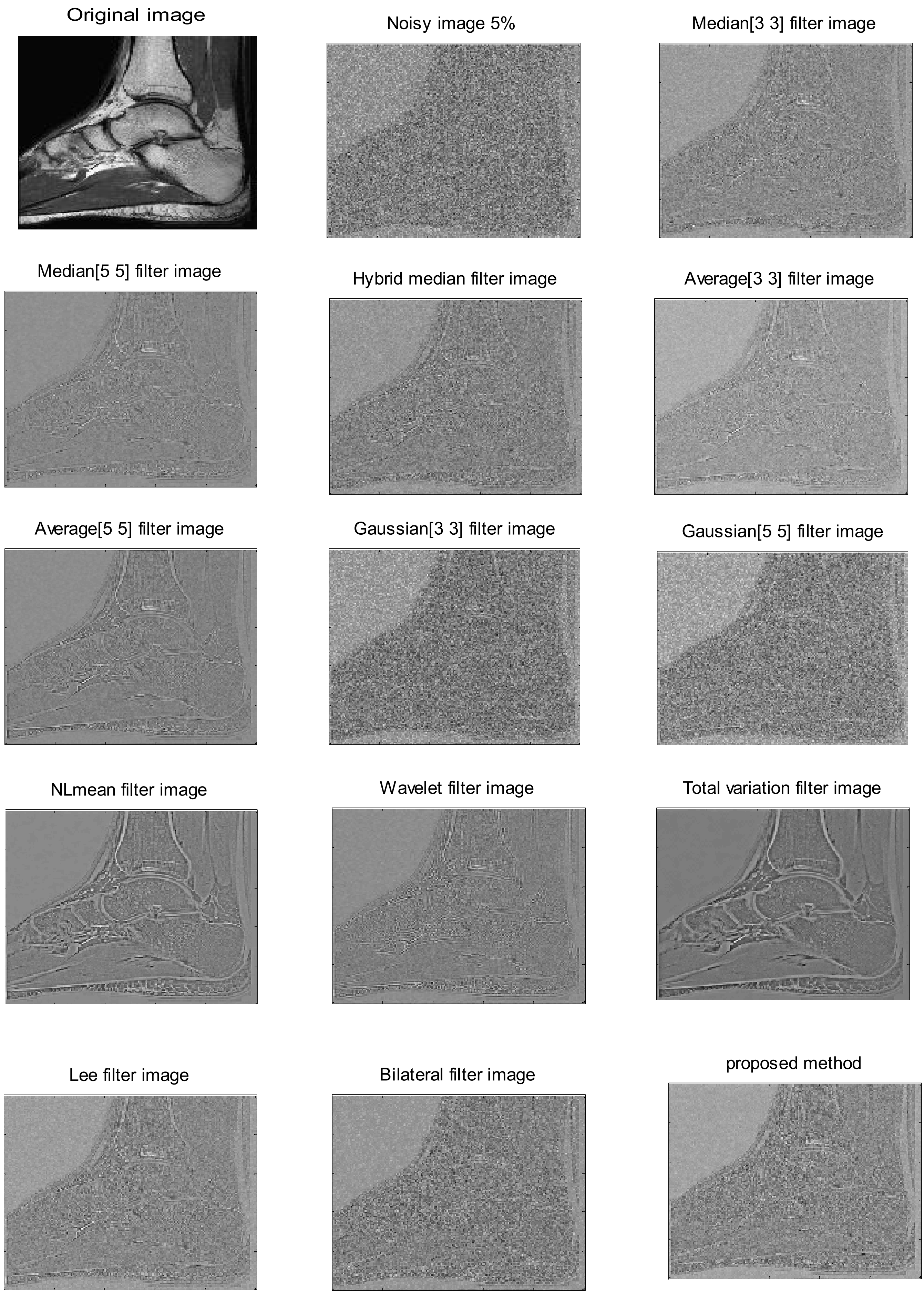
Original image
Noisy image 5%
Median[3 3] filter image
Median[5 5] filter image
Hybrid median filter image
Average[3 3] filter image
Average[5 5] filter image
Gaussian[3 3] filter image
Gaussian[5 5] filter image
NLmean filter image
Wavelet filter image
Total variation filter image
Lee filter image
Bilateral filter image
proposed method

Figure 5.5: Images method noise for Ankle MR Image 5%

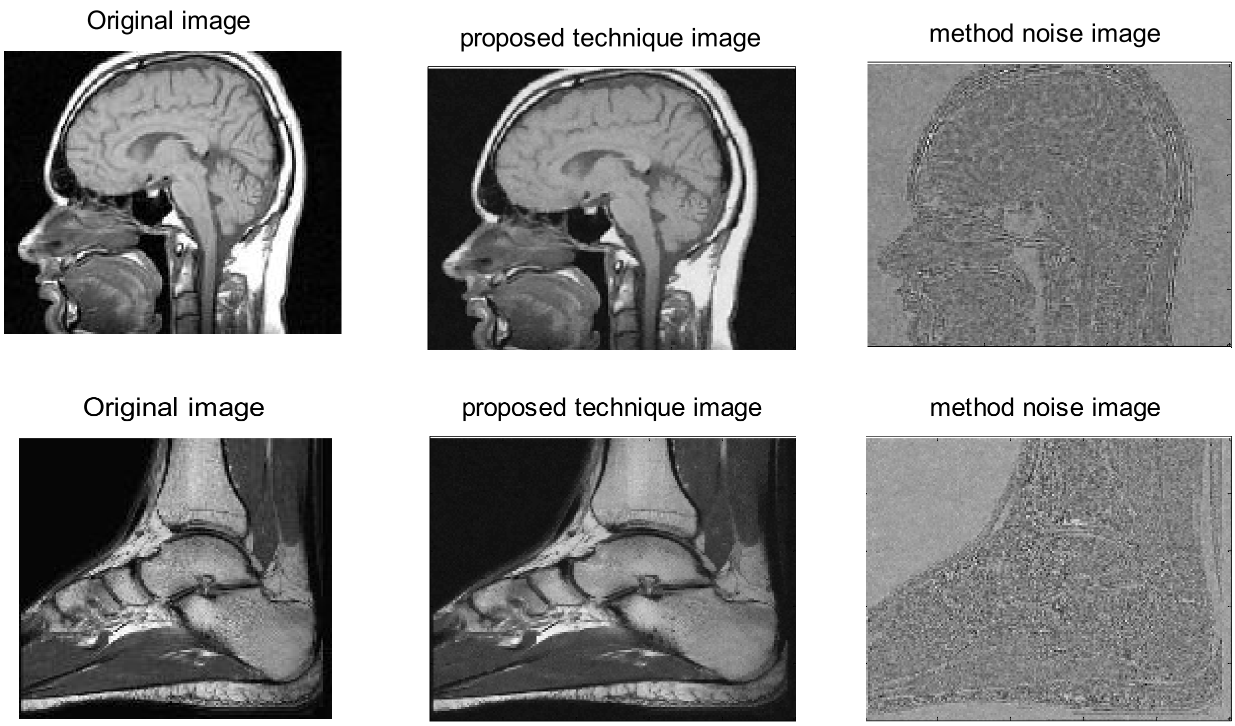

Figure 5.6: Real images experience. Two types of real MR Images (Brain and Ankle) denoised by proposed technique.

Table 5.1: The mean square error (MSE), signal to noise ratio (SNR) and university quality index (UQI) of Brain MR Image, at different noise levels, denoised by different techniques.

Image	Brain MR image 5% 250x300			Brain MR image 12% 250x300		
Metrices	MSE	SNR	UQI	MSE	SNR	UQI
Median [3 3]	0.04	21.36	0.669	0.09	14.62	0.531
Median [5 5]	0.06	18.33	0.594	0.09	14.19	0.503
hybrid Median	0.04	20.87	0.65	0.09	14.21	0.503
Average [3 3]	0.05	20.27	0.683	0.09	14.39	0.553
Average [5 5]	0.07	16.43	0.566	0.1	13.3	0.499
Gaussian [3 3]	0.04	21.37	0.655	0.1	13.38	0.474
Gaussian [5 5]	0.04	21.34	0.655	0.1	13.37	0.475
NL Mean	0.09	14.78	0.362	0.12	12.27	0.337
Wavelet	0.06	17.77	0.585	0.1	13.38	0.499
Total Variation	0.13	11.29	0.195	0.15	9.92	0.179
Lee	0.04	20.47	0.681	0.09	14.34	0.558
Bilateral	0.04	20.93	0.626	0.12	11.96	0.399
Proposed Technique	0.0378	22.13	0.699	0.092	14.4	0.527

Table 5.2: The mean square error (MSE), signal to noise ratio (SNR) and university quality index (UQI) of Ankle MR Image, at different noise levels, denoised by different techniques.

Image	Ankle MR image 5% 500x500			Ankle MR image 12% 500x500		
Metrices	MSE	SNR	UQI	MSE	SNR	UQI
Median [3 3]	0.03	20.72	0.578	0.08	13.29	0.404
Median [5 5]	0.04	19.25	0.467	0.08	13.62	0.365
hybrid Median	0.04	20.34	0.559	0.08	13.07	0.377
Average [3 3]	0.03	20.68	0.599	0.08	13.29	0.438
Average [5 5]	0.05	18.4	0.465	0.08	13.14	0.379
Gaussian [3 3]	0.04	20.15	0.578	0.1	11.79	0.349
Gaussian [5 5]	0.04	20.17	0.58	0.1	11.81	0.35
NL Mean	0.06	15.96	0.269	0.1	12.3	0.237
Wavelet	0.04	18.57	0.478	0.08	13.04	0.379
Total Variation	0.08	14.4	0.158	0.11	10.91	0.133
Lee	0.03	20.77	0.603	0.08	13.26	0.439
Bilateral	0.04	19.73	0.542	0.11	10.42	0.273
Proposed Technique	0.033	21.25	0.6	0.09	12.85	0.404

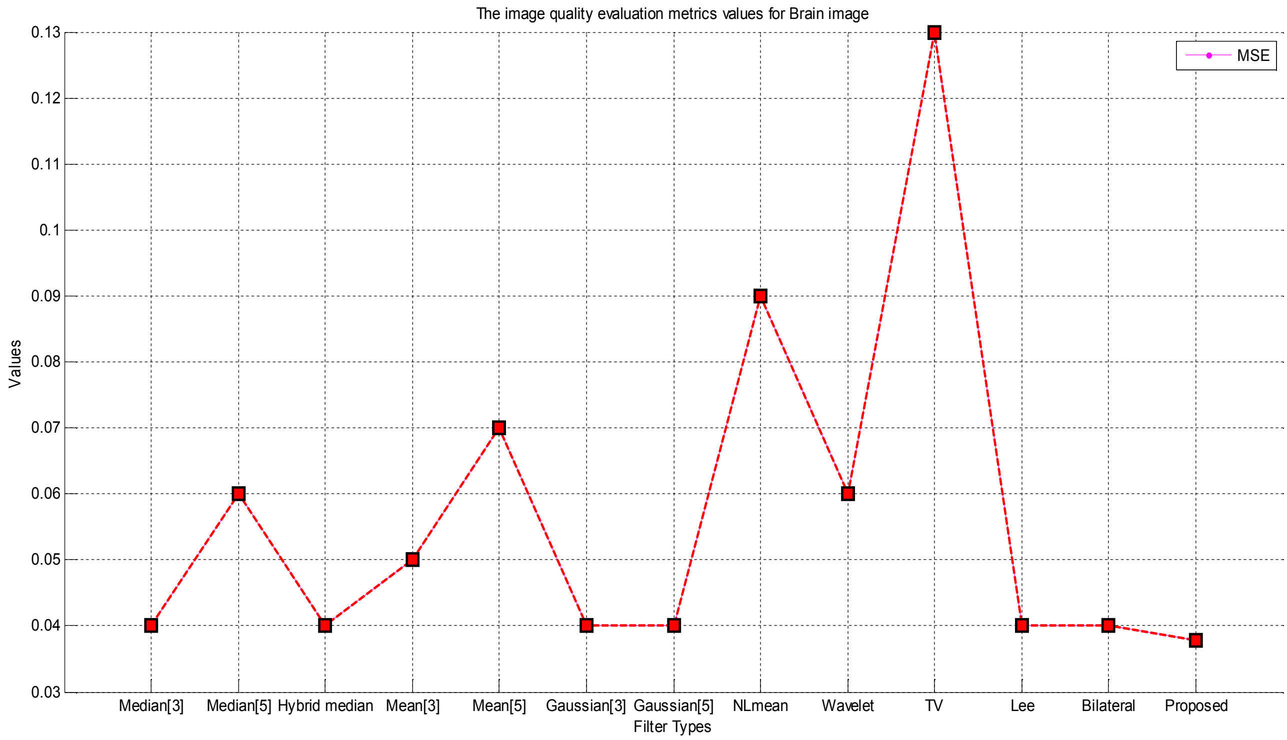

Figure 5.7: The MSE of Brain MR image at noise level 5%, denoised by different techniques.

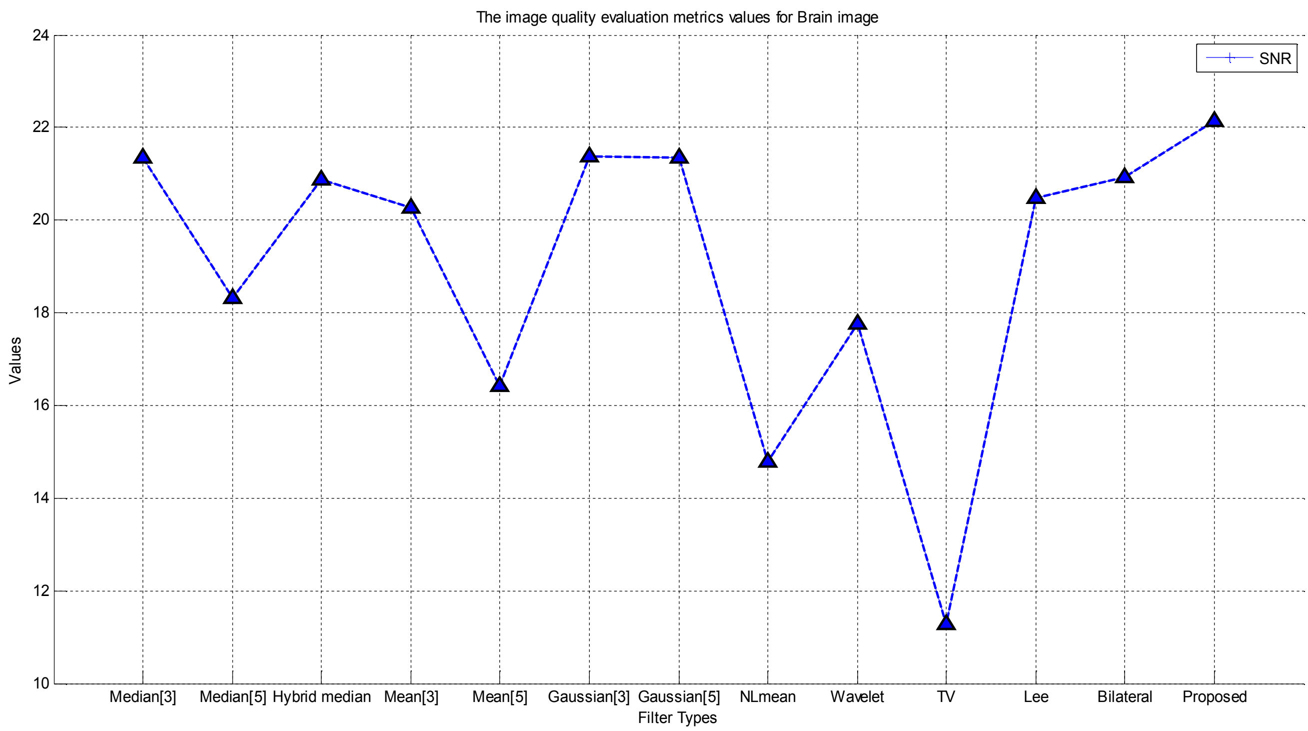

Figure 5.8: The SNR of Brain MR image at noise level 5%, denoised by different techniques.

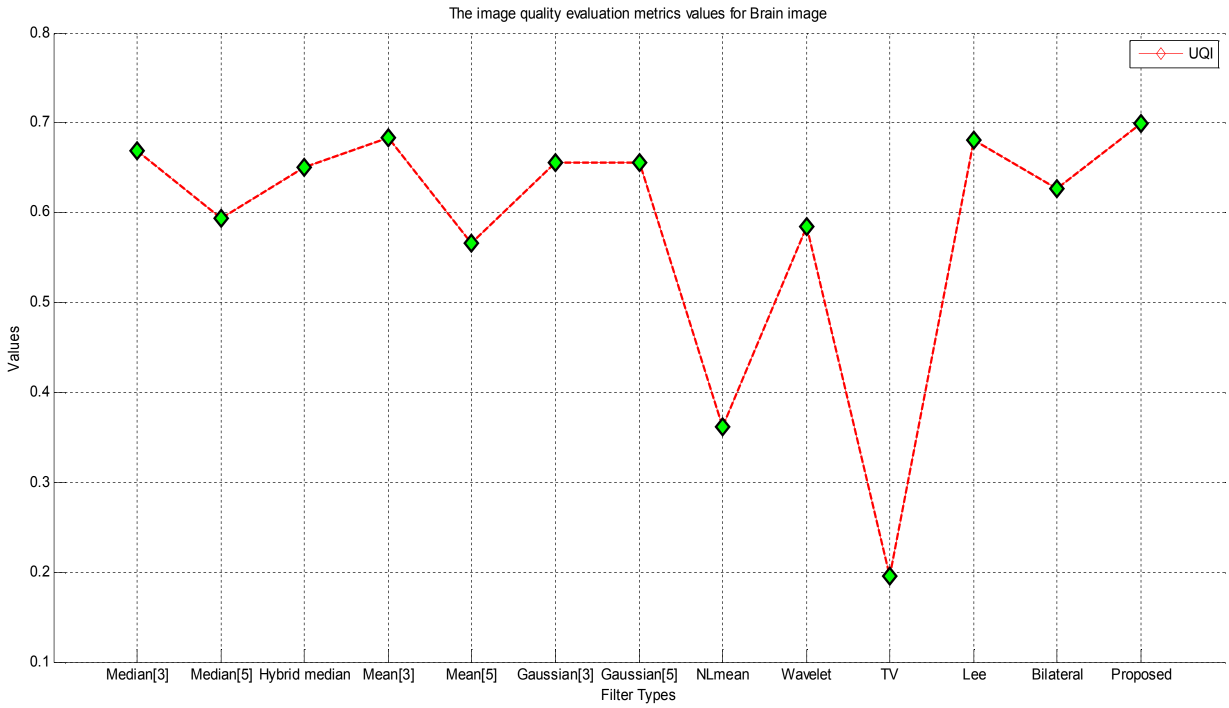

Figure 5.9: The university quality index (UQI) of Brain MR Image at noise level 5%, denoised by different techniques.

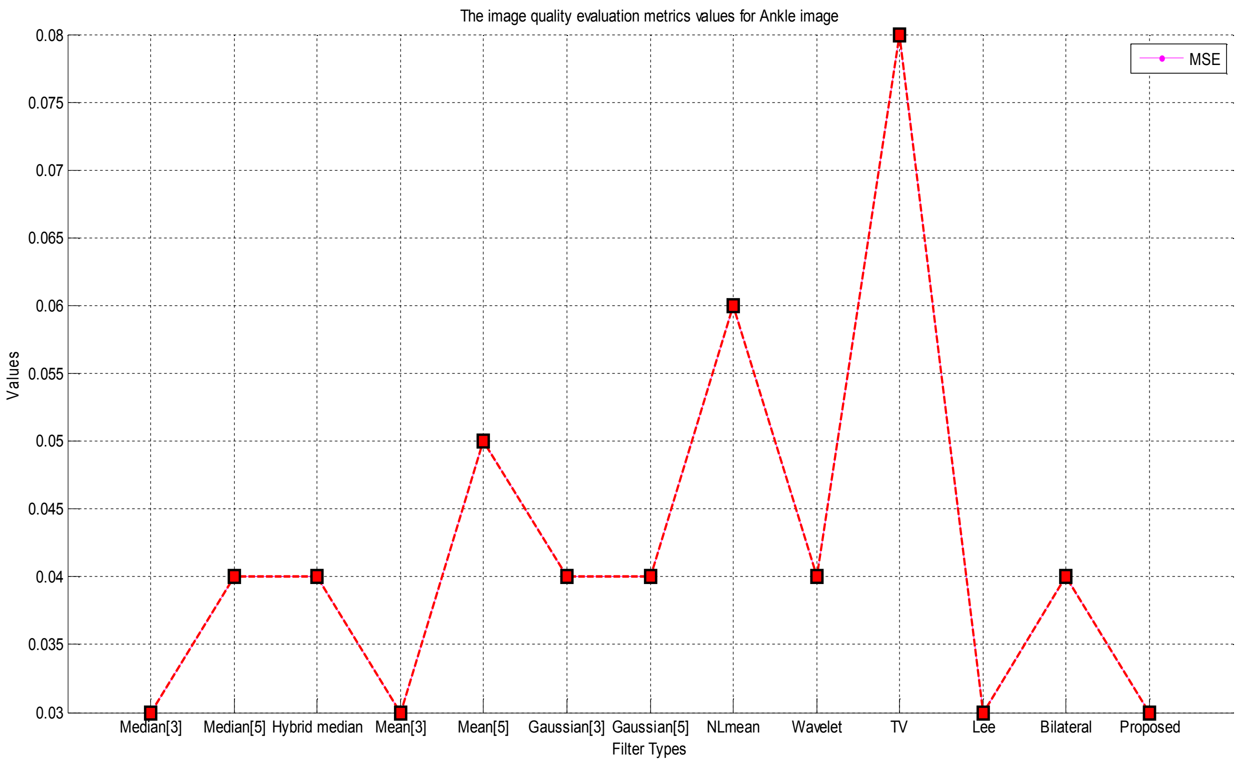

Figure 5.10: The MSE of Ankle MR Image at noise level 5%, denoised by different techniques.

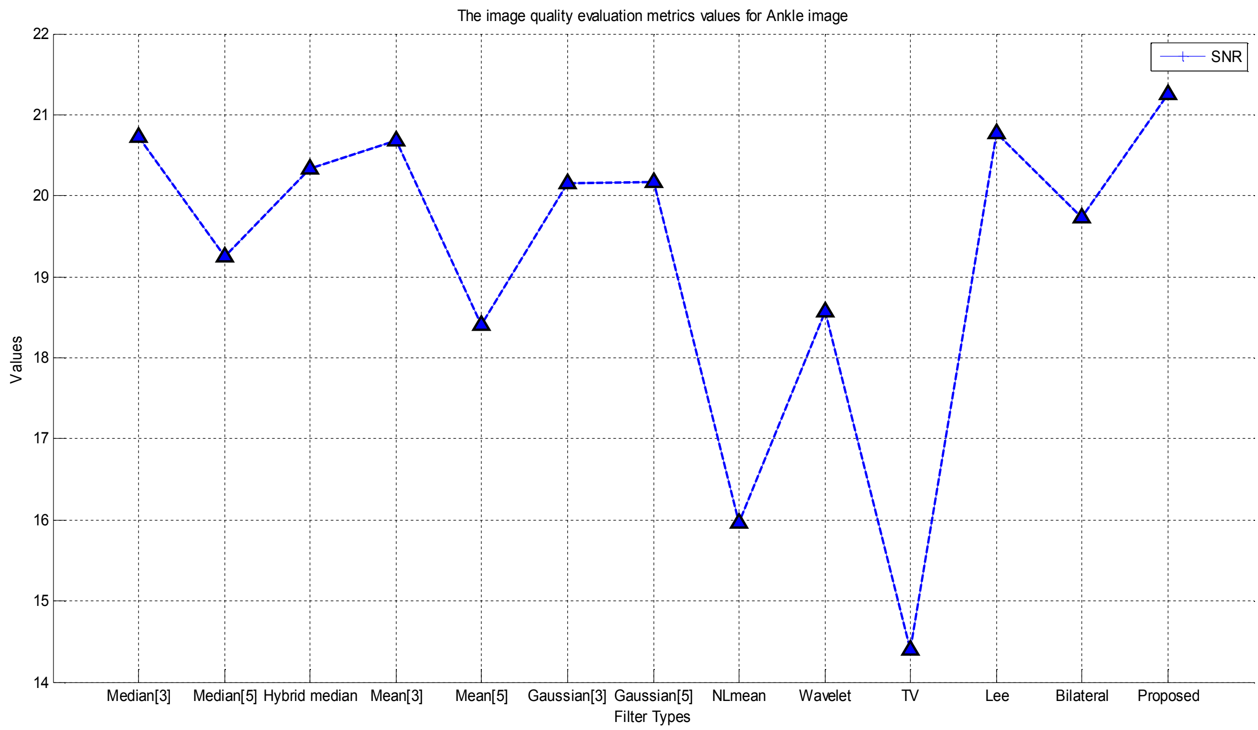

Figure 5.11: The SNR image of Ankle MR Image at noise level 5%, denoised by different techniques.

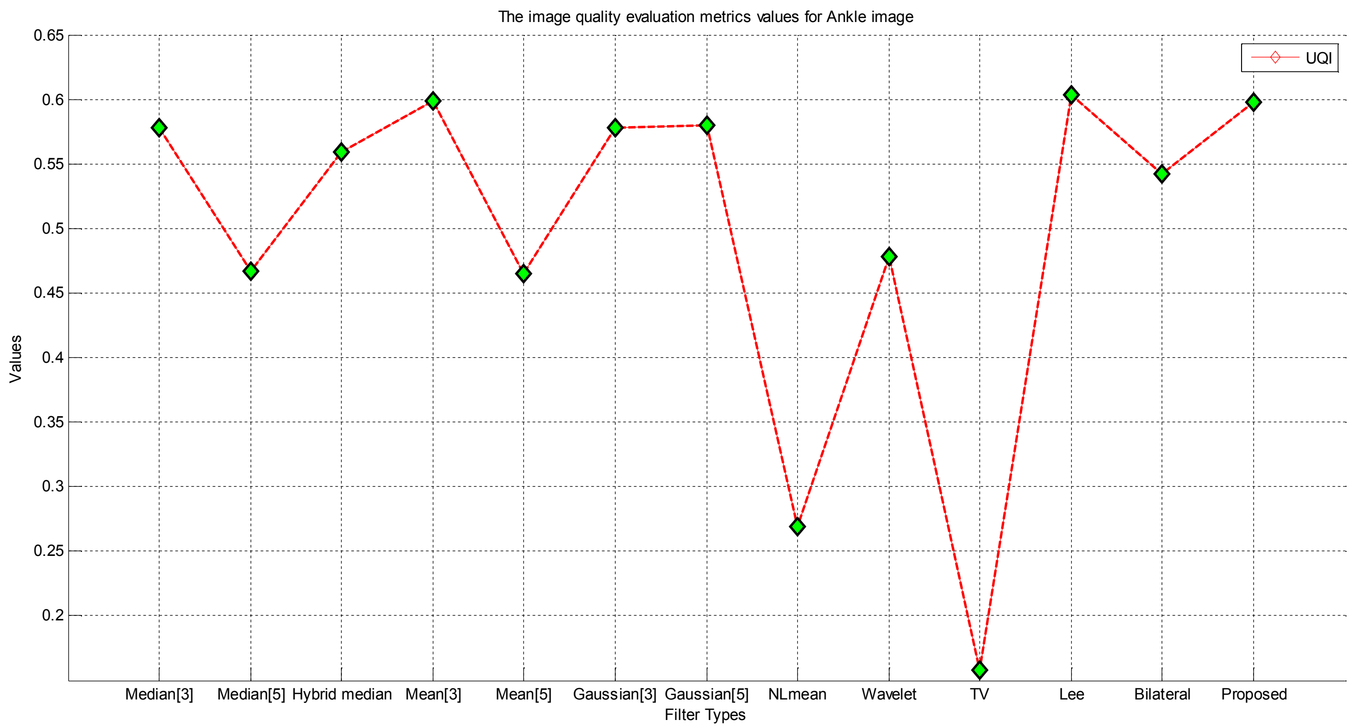

Figure 5.12: The university quality index (UQI) of Ankle MR Image at noise level 5%, denoised by different techniques.

5.5 Discussion

Chapter five dealing with the wavelet transform image denoising framework, which combines both the Bilateral filter and Lee filter. This framework, an image has been decomposed into low and high frequency components and applies wavelet sub-bands mixing. We can show the accurate result than other methods, the proposed algorithm gave promising results in producing cleaned images, keeping the main structures and details unaffected. The comparison with well-established methods such as Median, Hybrid median, Average (Mean), Gaussian, Non local mean, Wavelet, Total variation, Lee and Bilateral shows that the produces better result.

From tables: Table 5.1 and Table 5.2 it is observed that the proposed technique has lower MSE, higher SNR and higher UQI values as compared to other filters, the proposed technique is an excellent filter for suppressing low, moderate and high noise condition.

This quite evident from the observation Figures 5.7 to Figure 5.12 for MSE, SNR and UQI. Moreover, the visual quality of its output images is very good as observed in Figures 5.2 and Figure 5.3 the proposed technique is also seen to preserve fine details and edges and is seen not to yield unnecessarily high blurring effect in MR images. This is evident from Figure 5.6 for real MR images. As there is no measurement criteria that fully meet such requirements, visual inspection of the image residuals (i.e. the difference between the original and the filtered image) was used to evaluate filter efficacy, comparing the method noise of various filters, it is found in Figure 5.4 and Figure 5.5 that the proposed technique is good among all.

CHAPTER SEX

CONCLUSION AND FUTURE WORK

6.1 Conclusion

In this thesis, a study of MR image filtering techniques for rician noise reduction done by using different types of spatial and transform filters (Median, Hybrid Median, Average (Mean), Gaussian, Non local mean, Wavelet, Total variation, Lee and Bilateral) these filters are simulated on MATLAB, applied to different types of synthetic MR images and for evaluation these filters, the mean square error (MSE), signal to noise ratio (SNR), university quality index (UQI) and method noise are used as statistical parameters for analyze the filtering image. Also in this thesis, proposed a new scheme technique by the wavelet transform and inverse wavelet transform to reduction rician noise, this method simulated on MATLAB, applied to different types of synthetic and real MR images, the MSE, SNR, UQI and method noise are taken as performance measure, a comparison between it and filters that say previously was made, in this comparison different noise levels (5% Rician noise and 12% Rician noise) were taken to demonstrate that the proposed method or technique is capable to reduce noise very perfect at low, moderate and high noise levels compare to other filtering techniques. Also an observation in the final result of output image by using proposed technique have higher UQI, higher SNR and low MSE values as compared to other filters, moderate and high noise levels. The method noise should preserve as many features as possible of the original image and look as much as possible like Rician noise and proposed technique achieved this very well.

The proposed technique algorithm provides brilliant results in producing cleaned images, keeping the main features, preserve fine details and edges and is seen not to yield unnecessarily high blurring effect in MR images.

6.2 Future work

Some new directions of thesis in the field of image denoising are not yet fully explored. There is sufficient scope to develop very effective filters in the directions mentioned below:

- Some other transforms such as discrete Hartley transform, curvelet and slantlet can be used for image denoising.
- May be done by considering the technique of incorporating neighbour multiwavelet coefficients in the thresholding process for multiwavelet image denoising.

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