



Sudan University of Science and Technology

Faculty of graduate studies

Master of Biomedical Engineering

Filtering Computed Tomography Images by Using An Adaptive Hybrid Technique

ترشيح صورالأشعه المقطعيه باستخدام طريقه تلاذميه مهجنة

This thesis for the fulfillment of the requirement for M.sc Degree in Biomedical Engineering

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First and foremost, thanks Allah.

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ABSTRACT:

Medical images are generally noisy due to the physical mechanisms of the acquisition process. In Computed tomography (CT) scan there is a scope to adapt patient image quality and dose. Reduction in radiation dose (i.e. the amount of X-rays) affects the quality of image and is responsible for image noise in CT. Most of the de-noising algorithms assume additive Gaussian noise.

This thesis contains a comparative analysis of a number of de-noising algorithms namely wiener filtering, Average filtering, antistropic filtering, Bilateral filtering, median filtering, Wavelet filtering, Total variation filtering and convential antistropic filtering. Then, some quantitative performance metrics like Mean Square Error (MSE), Root Mean Square Error (RMSE), Signal to Noise Ratio (SNR), and Peak Signal to Noise Ratio (PSNR) were computed and compared with the previous filters mentioned, The noise were computed and compared for 3different values 3%,5% and7%.

This comparison helps in the assessment of image quality and fidelity; it concludes that the bilateral filtering is the most efficient method in removing Gaussian noise from CT scan images.

The proposed method combines the bilateral filter and the wavelet decomposition transform to obtain better results than all the other filters compared.

المستخلص:

الصور الطبية تحتوي على ضوضاء عموما بسبب الأليات الفيزيائيه المستخدمه في عمليه استخلاصها.في التصوير المقطعي (CT) هنالك مجال للتكييف بين جودة الصورة المرضى والجرعه المعطاه للمريض, تخفيض جرعة الإشعاع (أي كمية من الأشعة السينية) يؤثر على جودة الصورة وهو المسؤول عن الضوضاء في الصوره الناتجه من التصوير المقطعي. معظم خوارزميات ازاله الضوضاء تعمل على ضجيج جاوس.

تحوي هذه الرسالة تحليلا مقارنا لعدد من خوار زميات دي ازاله الضوضاء وهي:مرشح وينر (antistropic filtering) ، ومتوسط الترشيح (Average filtering) ، والترشيح متباين الخواص (median filtering)، متوسط الترشيح (Bilateral filtering)، وتصفية المويجات (median filtering) ، مجموع تصفية الاختلاف (Total variation filtering) والترشيح متباين الخواص التقليدية (filtering)، مجموع تصفية الاختلاف (convential antistropic filtering) والترشيح متباين الخواص التقليدية (شكل متوسط مربع الخطأ (MSE)، جذر متوسط مربع الخطأ (RMSE) ، نسبة الإشارة إلى الضوضاء (SNR) ، وقمة نسبة الإشارة إلى الضوضاء (PSNR) .

تم حساب ومقارنة مع المرشحات السابقة الذكر، ومن ثم احتساب الضوضاء لثلاثه قيم مختلفة 3,2%,7%. هذه المقارنة تساعد في تقييم جودة الصورة خلصت المقارنه إلى أن تصفية الثنائية هي الطريقة الأكثر فعالية في إزالة الضوضاء الضبابي من صور الاشعة المقطعية مقارنه مع بقيه المرشحات المستخدمه.

ووجد ان الطريقه المقترحه التي تعمل علي الدمج بين المرشح الثنائي (Bilateral filtering)وتحلل المويجات (wavelet decomposition) تعطي نتائج افضل من استخدام طريقه التصفيه الثنائيه لوحدها.

Abbreviations:

CT:Computed Temography.

MSE : Mean Square Error .

RMSE: Root Mean Square Error.

SNR: Signal to Noise Ratio.

PSNR: Peak Signal to Noise Ratio

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Chapter one

Introduction

1.1 Introduction:

Image processing concept play an important role in the field of Medical diagnosis of diseases. Noise is introduced in the medical images due to various reasons. In Medical Imaging, Noise degrades the quality of images. This degradation includes suppression of edges, blurring boundaries etc. Edge and preservation details are very important to discover a disease [1]. Images are often corrupted with noise during the acquisition of image, during transmission of image, and retrieval from any storage media. Noise in digital image often occurs during the acquisition of image due to Sensor (e.g., thermal or electrical interference) and Environmental conditions (rain, snow etc.). Most natural images are assumed to be corrupted by Gaussian Noise, Salt and Pepper Noise and image Blur ness, Impulse Noise etc[2]. The presence of noise gives an image a mottled, grainy, textured or snowy appearance [3]. Therefore; the problem of recovering an original image from noisy image has received an ever increasing attention in recent years [4]. The recovering can be accomplished by image de-noising, a process of estimating the original image from an image that has been contaminated by noise degradation [5]. Medical imaging common application of X-ray is CT. Its cross sectional images are used for diagnostic and therapeutic purposes in various medical disciplines to obtain a precise images to facilitate accurate Observation. Two important characteristics of the computed topographic (CT) image that affect the ability to visualize anatomic structures and pathologic features are blur and noise[6]. Since its introduction in 1972, computed tomography has seen several generations of improvements, including multi detector row helical CT, improved spatial and temporal resolution, dual energy CT, and iterative reconstruction. Many artifacts from the early days of CT are now substantially reduced, but some artifacts remain, and new technologies have introduced new, incompletely characterized artifacts, all this artifact affect the quality of the CT image [7].

1.2 Problem Definition:

The noise in computed tomography image ultimately limits the ability of the radiologist to discriminate between two regions of different density. Because of its unpredictable nature, such noise cannot be completely eliminated from the image and will always lead to some uncertainty in the interpretation of the image .The x-ray computed topographic (CT) scanner has made it possible to detect the presence of lesions of very low contrast.

1.3 Objectives of Study:

1.3.1 General objective:

Use An adaptive Hybrid Technique for Filtering Computed Tomography Images.

1.3.2 Specific objective:

To use Hybrid filter which is combination of the wavelet decomposition and bilateral Filter on the images and observe the change in MSE, RMSE, PSNR ratio and SNR ratio.

1.4 Thesis Layout

This thesis consists of six chapters:

Chapter one: Introduction, introduces the problem and the objectives of the thesis.

Chapter two: Theoretical Background defines the CT scan uses, image production and reconstruction, image enhancement.

Chapter three: Literature Review

Chapter four: Methodology.

Chapter five: Results and discussion of the proposed de-noising method.

Chapter six: Conclusions and recomendation.

Chapter two

Theoretical Background

2.1 CT Scan:

Computed Tomography (CT) is a test that combines X-rays with a computer to create images that appear as slices. The result is a detailed picture that may show problems with soft tissue (such as the lining of the sinuses), organs (such as the brain, liver, kidneys or lungs) and bones [8].

2.1.1 Uses of CT:

CT scans can produce detailed images of many structures inside the body, including the internal organs, blood vessels and bones. They can be used to:

- diagnose conditions including damage to bones, injuries to internal organs,
 problems with blood flow, <u>strokes</u> and <u>cancer</u>
- **guide further tests or treatments** for example, CT scans can help to determine the location, size and shape of a tumor before having <u>radiotherapy</u>, or allow a doctor to take a needle <u>biopsy</u> (where a small tissue sample is removed using a needle) or drain an <u>abscess</u>
- monitor conditions including checking the size of tumors during and after cancer treatment

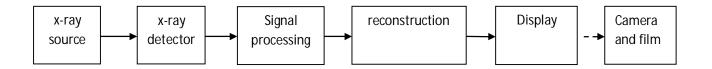
CT scans wouldn't normally be used to check for problems if you don't have any symptoms (known as screening). This is because the benefits of screening may not outweigh the risks, particularly if it leads to unnecessary testing and anxiety[9].

2.1.2CT Scan Image:

Steps in the production of CT image:

- 1. Data acquisition.
- 2. Image reconstruction.

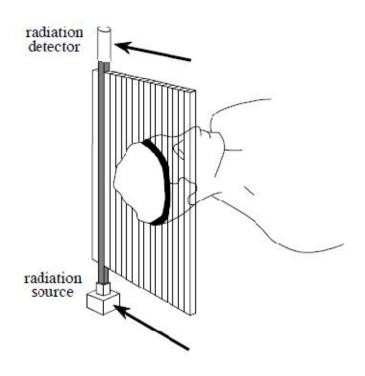
3. Image display, manipulation, storage, communications and recording[10]



Figure(2.1) Block diagram of the steps involved in obtaining a CT image.

2.1.3 CT Data Acquisition:

A simple CT system passes a narrow beam of x-rays through the body from source to detector. The source and detector are then translated to obtain a complete view. The remaining views are obtained by rotating the source and detector in about 1 E increments, and repeating the translation process[11].



Figure(2.2) simple CT system passes a narrow beam of x-rays through the body from source to detector.

2.1.4 Image Reconstruction:

The foundation of the mathematical package for image reconstruction is the reconstruction algorithm, which may be one of four types.

- 1. Simple back projection: In this method, each x-ray transmission path through the body is divided into equally spaced elements, and each element is assumed to contribute equally to the total attenuation along the x-ray path. By summing the attenuation for each element over all x-ray paths that intersect the element at different angular orientations, a final summed attenuation coefficient is determined for each element. When this coefficient is combined with the summed coefficients for all other elements in the anatomic section scanned by the x-ray beam, a composite image of attenuation coefficients is obtained. Although the simple back projection approach to reconstruction algorithms is straight forward, it produces blurred images of sharp features in the object.
- 2. **Filtered back projection**: This reconstruction algorithm, often referred to as the convolution method, uses a one-dimensional integral equation for thereconstruction of a two-dimensional image. In the convolution method of using integral equations, a deblurring function is combined (convolved) with the x-ray transmission data to remove most of the blurring before the data are back projected. The most common deblurring function is a filter that removes the frequency components of the x-ray transmission data that are responsible for most of the blurring in the composite image. One of the advantages of the convolution method of image reconstruction is that the image can be constructed while x-ray transmission data are being collected. The convolution method is the most popular reconstruction algorithm used today in CT.
- 3. **Fourier transform:** In this approach, the x-ray attenuation pattern at each angular orientation is separated into frequency components of various amplitudes, similar to the way a musical note can be divided into relative contributions of different frequencies. From these frequency components, the entire image is assembled in "frequency space" into a spatially correct image and then reconstructed by an inverse Fourier transform process.

4. **Series expansion:** In this technique, variations of which are known as ART (algebraic reconstruction technique), ILST (interactive least-squares technique), and SIRT (simultaneous iterative reconstruction technique), x-ray attenuation data at one angular orientation are divided into equally spaced elements along each of several rays. These data are compared with similar data at a different angular orientation, and differences in x-ray attenuation at the two orientations are added equally to the appropriate elements. This process is repeated for all angular orientations, with a decreasing fraction of the attenuation differences added each time to ensure convergence of the reconstruction data. In this method, all x-ray attenuation data must be available before reconstruction can begin.

2.2 Noise Produced in The Image:

There are several types of image "noise" that can interfere with the interpretation of an image. Although noise may infiltrate and corrupt the data at any point in the CT process, the ultimate source of noise is the random, statistical noise, arising from the detection of a finite number of x-ray quanta in the projection measurements.

Random noise: appears **as** fluctuations in the image density, The radiologist is familiar with random noise in the form of radiographic mottle found in standard radiographs taken with fast screen-film combinations.

Statistical noise: in x-ray images arises from the fluctuations inherent in the detection of a finite number of x-ray quanta. Statistical noise may also be called quantum noise and is often referred to as quantum mottle in film radiography Statistical noise clearly represents a fundamental limitation in x-ray radiographic processes. The only way to reduce the effects of statistical noise is to increase the number of detected x-ray quanta. Normally this is achieved by increasing the number of transmitted x rays through an increase in dose.

Electronic noise: In processing electric signals, electronic circuits inevitably add some noise to the signals. Analog circuits, those which process continuously varying signals, are most susceptible to additional noise. The difficulty of noise suppression is compounded by

the fact that for some types of x-ray detectors, the electronic signals are very small. There is evidence (Cohen, 1979) that many commercially available CT scanners are sufficiently well engineered to reduce the con- tribution of electronic noise under normal operating conditions to a fraction of the statistical noise contribution. The signals are converted to digital or discrete form in the signal-processing step and then sent to a computer for reconstruction. Digital circuits, those which process discrete signals as in digital computers, are relatively impervious to electronic noise problems.

Roundoff errors: Although digital computers are not subject to electronic noise, they do introduce noise in the reconstruction process through roundoff errors. The errors arise from the limited number of bits used to represent numbers in the computer. For example, the product of two numbers must be rounded off to the least significant bit used in the computer's representation of the number. Roundoff errors can normally be kept at an insignificant level either through choice of a computer with enough bits per word or through proper programming. It should be pointed out that in some CT scanners the final reconstruction is stored with the least significant bit equal to one CT number (0.1 % of the linear attenuation coefficient of water). This should not influence the accuracy significantly so long as the rms noise is greater than one CT number.

Artifactual noise: Artifacts might be viewed as a form of noise in that they interfere with the interpretation of the CT image. Their presence is often indicated by a readily identifiable pattern, for example, in the case of streak artifacts. These identifiable artifacts do not produce random noise, since they should be unchanged in repeated scans of the same object. However, there are instances in which regions of a reconstruction may experience an increase in variance due to nonparent artifacts (Sheridan et al., 1980).

Structural "noise": Density variations in the object being imaged that interfere with the diagnosis are sometimes referred to as structural "noise" or structural clutter. In standard radiography a large amount of structural clutter is produced by the superposition of various anatomic structures, The CT technique eliminates most of this superposition, but the

radiologist should be aware that partial contributions may be introduced by structures that principally appear in adjacent CT slices. Some organs, such as the liver, may have density variations within them that have the appearance of random noise. Although the texture pattern of the organ may not be reproducible from one CT scan to the next because of patient motion, this type of structural variation is, of course, not random [10].

2.3 Noise in CT Image:

This most common type of noise in CT and the one used in this research is Gaussian noise. The noise has a probability density function [PDF] of the normal distribution. It is also known as Gaussian distribution. It is a major part of the read noise of an image sensor that is of the constant level of noise in the dark areas of the image [2].

Gaussian noise:

$$P(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(z-\mu)^2/2\sigma^2}$$
 (2.1)

Where

z is Gray level.

 σ is the Stander Deviation.

 μ is Mean of average value of z.

 σ^2 is Variance.

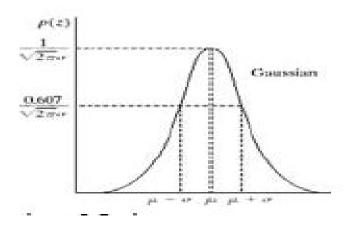


Figure (2.3) PDF of Gaussian Noise

2.4 Image Quality Metrics:

Image quality assessment is an emerging field of signal processing .More or less defined as the task of designing an algorithm to automatically judge the perceived "quality" of an image.

A-The Mean Squared Error (MSE):

The MSE represents the average of the squares of the "errors" between our actual image and our noisy image.

The error is the amount by which the values of the original image differ from the degraded image.

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{m-1} ||f(i,j) - g(i,j)||^2$$
(2.2)

where

f represents the matrix data of our original image

 \mathbf{g} represents the matrix data of our degraded image in question

m represents the numbers of rows of pixels of the images and i represents the index of that row **n** represents the number of columns of pixels of the image and j represents the index of that column[12]

B-Signal To Noise Ratio (SNR):

The relative amount of signal and noise present in a waveform is usually quantified by the signal-to-noise ratio, *SNR*. As the name implies, this is simply the ratio of signal to noise, both measured in RMS (root-mean-squared) amplitude. The SNR is often expressed in "db" (short for decibels)[13] where:

$$SNR = 20\log\left(\frac{signal}{noise}\right) \tag{2.3}$$

C-Peak Signal-To-Noise Ratio (PSNR):

Is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. Because many signals have a very wide dynamic range, (ratio between the largest and smallest possible values of a changeable quantity) the **PSNR** is usually expressed in terms of the logarithmic decibel scale.

The mathematical representation of the **PSNR** is as follows:

$$PSNR = 20log_{10} \left(\frac{MAX_f}{\sqrt{MSE}} \right)$$
 (2.4)

where

MSE (Mean Squared Error)

MAXf is the maximum signal value that exists in our original "known to be good" image.[12]

D- The Root Mean Square (RMS):

The Root Mean Square Error computes the mean squared pixel-wise difference in intensity between image A and B over a region. It is simple to compute and has a relatively large capture radius, but even linear changes in intensity can result in a poor match. The formulae for calculated image matrices are:

$$MSE = \frac{1}{N.M} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} [f(x, y) - f^*(x, y)]$$
 (2.5)

$$RMSE = \sqrt{MSE} \tag{2.6}$$

Where f (x, y) is the input image data and $f^*(x, y)$ is block of the reference image. M and N are the matrix dimensions in x and y, respectively [14].

2.5 The Digital Image Processing:

An image may be defined as a two-dimensional function, f(x, y), where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point [14]. Image enhancement can be performed for several reasons. One is simply to make the image easier to visually examine and interpret. Many of the procedures described here are based to some degree on the response or the requirements of the human visual system. Some are purely ad hoc methods that have been found over time to be useful. Others are based on the physics of image generation (e.g., light interaction with subjects) or the operation of optical Components and image detectors (e.g., removing distortion or correcting for the response of Solid state cameras). The latter are not necessarily more complicated to apply.

2.5.1 Image Subtraction:

The difference between two images f(x, y) and h(x, y), expressed as

$$g(x, y) = f(x, y) - h(x, y)$$
 (2.7)

is obtained by computing the difference between all pairs of corresponding pixels from f and h. The key usefulness of subtraction is the enhancement of differences between images. where we showed that the higher-order bit planes of an image carry a significant amount of visually relevant detail, while the lower planes contribute more to fine (often imperceptible) detail[15].

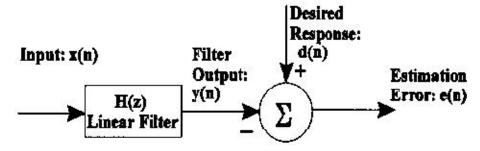
2.5.2Meadian Filter (DsFmedian):

The filter DsFmedian is a median filter applied over windows of size 5×5 . This is an extension of the filter DsFhmedian, computes the median of the outputs generated by median filtering with three different windows (cross shape window, x-shape window and normal window). The moving size window for the despeckle filter DsFmedian and

DsFhmedian was for both filters 5×5 pixels,while the number of iterations applied to each image was three and two respectively. The DsFmedian filter is well suited for improving the optical perception evaluation but repeated application destroys the image edges. The filter DsFhmedian preserves the edges and increases the optical perception evaluation [16].

2.5.3Wiener Filter:

The basic concept behind Wiener filter theory is to minimize the difference between the filtered output and some desired output. This minimization is based on the least mean square approach, which adjusts the filter coefficients to reduce the square of the difference between the desired and actual waveform after filtering.



Figure(2.4)Basic arrangement of signals and processes in a Wiener filter.

The convolution equation is:

$$y(n) = \sum_{k=1}^{L} b(k)x(n-k)$$
 (2.8)

Where h(k) is the impulse response of the linear filter. The output of the filter, y(n), can be thought of as an estimate of the desired signal, d(n). The difference between the estimate and desired signal[13].

2.5.4 Anisotropic Diffusion Filter (DsFsrad):

It is based on setting the diffusion coefficient in the diffusion equation using the local frame gradient and the frame Laplacian. by extending the PDE versions of the despeckle filter as:

$$f_{i,j} = g_{i,j} + \frac{1}{\eta_s} div(c_{srad}(|\nabla g|) \nabla g_{i,j})$$
(2.9)

where η_s is the size of the filtering window. The diffusion coefficient for the speckle anisotropic diffusion, c_{srad} is given as:

$$c_{srad}^{2}(|\nabla g|) = \frac{\left(\frac{1}{2}\right)|\nabla g_{i,j}|^{2} - \left(\frac{1}{16}\right)(\nabla^{2}g_{i,j})^{2}}{(g_{i,j} + (1/4)\nabla^{2}g_{i,j})^{2}}$$
(2.10)

It is required that c_{srad} ($|\nabla g|$) ≥ 0 . The above instantaneous coefficient of variation combines a normalized gradient magnitude operator and a normalized Laplacian operator to act like an edge detector[17].

2.5.5 Convential Anisotropic Diffusion (ANISODIFF):

Anisotropic diffusion is a shape adaptive filtering technique whereby an image is evolved under an edge controlled diffusion operator where the orientation of the filter is determined by the local gradient in the image. Image details such as edges and lines are thus preserved or even enhanced, while regions within edges are smoothed . The generalised diffusion

equation is given by:

$$\frac{\partial}{\partial t}I(x,y,t) = div(c(x,y,t)\nabla I(x,y,t)) \tag{2.11}$$

$$I(x,y,0)=I_0(x,y)$$
 (2.12)

where r denotes the image gradient, div(c(x, y, t)) is the divergence operator and c(x; y; t) is the diffusivity function, controlling the rate of diffusion. Perona and Malik [18]

proposed that c(x; y; t) be chosen as a function of the image gradient, such that image edges are preserved:

$$c(x, y, t) = 1/(1 + \frac{|\nabla I|^2}{K^2})$$
 (2.13)

Where K is a contrast parameter and is determined automatically using the noise estimator described by Canny.

2.5.6 Total Variation Filter(TV):

Rudin et al. proposed Total variation (TV) [19] which is a constrained optimization type of numerical algorithm for removing noise from images. The total variation of the image is minimized subject to constraints involving the statistics of the noise. The constraints are imposed using Lagrange multipliers. The solution is obtained using the gradient-projection method. This amounts to solving a time dependent partial differential equation on a manifold determined by the constraints. As $t\rightarrow\infty$ the solution converges to a steady state which is the denoised image. In total variation algorithm, the gradients of noisy image, g(x,y) in four directions (East, West, North and South) are calculated. The gradients in all four directions are calculated as follows

$$\nabla_N g(x, y) = \left(g(x, y) - g(-1, y)\right) \tag{2.14}$$

$$\nabla_S g(x, y) = \left(g(x+1, y) - g(x, y)\right) \tag{2.15}$$

$$\nabla_W g(x, y) = \left(g(x, y) - g(x, -1)\right) \tag{2.16}$$

$$\nabla_E g(x, y) = \left(g(x, y + 1) - g(x, y)\right) \tag{2.17}$$

where, ∇g is the gradient operator

The noisy image undergoes several iterations to suppress AWGN.

The resulted output image after (n+1) iterations is expressed as:

$$\hat{f}(x,y) = g^{-n+1}(x,y) \tag{2.18}$$

2.5.7 Wavelet Thresolding Filter:

Wavelet thresholding is one of the most popular approaches. In wavelet thresholding, a signal is decomposed into its approximation (low-frequency) and detail (high-frequency) sub-bands; since most of the image information is concentrated in a few large coefficients, the detail s sub-bands are processed with hard or soft thresholding operations [20].

Suppose we measure a noisy signal

$$x = s + v \tag{2.19}$$

Assume s has a sparse representation in a certain wavelet bases, and $v \sim p(0, \sigma^2 I)$

SO:

$$y = W^{T}x = W^{T}s + W^{T}v = p + z (2.20)$$

Most elements in p are 0 or close to 0, and $z \sim N(0, \sigma^2 I)$

Since W is orthogonal, the estimation problem amounts to recovery of a signal in Gaussian noise. As p is sparse, one method is to apply a Gaussian mixture model for p. Assume a prior $p \sim aN(0, \sigma_1^2) + (1 - a)N(0, \sigma_2^2), \sigma_1^2$ is the variance of "significant" coefficients, and is σ_2^2 the variance of "insignificant" coefficients.

Then

$$\check{p} = E\left(\frac{p}{y}\right) = \tau(y)y, \tau(y) \tag{2.21}$$

is called the shrinkage factor, which depends on the prior variances σ_1^2 and σ_2^2 . The effect of the shrinkage factor is that small coefficients are set early to 0, and large coefficients are unaltered. Small coefficients are mostly noises, and large coefficients contain actual signal.

2.5.8 Bilateral Filter:

The bilateral filter computes the filter output at a pixel as a weighted average of neighboring pixels. It smoothes the image while preserving edges. Due to this nice property, it has been widely used in noise reduction, HDR compression [21], multi-scale detail decomposition, and image abstraction [22]. It is generalized to the joint bilateral filter in [23], in which the weights are computed from another guidance image rather than the filter input. The joint bilateral filter is particular favored when the filter input is not reliable to provide edge information, e.g., when it is very noisy or is an intermediate result. The joint bilateral filter is applicable in flash/no-flash de-noising [23], image up sampling [26], and image deconvolution [27]. However, it has been noticed [21, 24] that the bilateral filter may have the gradient reversal artifacts in detail decomposition and HDR compression. The reason is that when a pixel (often on an edge) has few similar pixels around it, the Gaussian weighted average is unstable. Another issue concerning the bilateral filter is its efficiency. The brute-force implementation is in O(Nr2) time, which is prohibitively high when the kernel radius r is large. In [25] an approximated solution is obtained in adiscretized space-color grid. Recently, O(N) time algorithms [22,26] have been developed based on histograms. Adam set al. [22] proposes a fast algorithm for color images. All the above methods require a high quantization degree to achieve satisfactory speed, but at the expense of quality degradation.

The bilateral filtering kernel w^{bf} is given by:

$$W_{ij}^{bf}(I) = \frac{1}{K_I} \exp\left(-\frac{|X_i - X_j|^2}{\sigma_s^2}\right) \exp\left(-\frac{|I_i - I_j|^2}{\sigma_r^2}\right)$$
(2.22)

where x is the pixel coordinate, and Ki is a normalizing parameter to ensure that $\sum_j w_{ij}^{bf} = 1$ The parameters σ_s^2 and σ_r^2 adjust the spatial similarity and the range (intensity/color) similarity respectively. The joint bilateral filter degrades

to the original bilateral filter when I and p are identical.

2.6Wavelet Decomposition:

In practical, we often want to get its multi-stage decomposition for a small wave, so that we can have a more accurate analysis of wavelet. Then we will introduce the multi-level of wavelet decomposition specifically, we will introduce the multistage decomposition diagram and multistage decomposition algorithm, so that we can get more profound understanding from the multistage decomposition of wavelet[27]

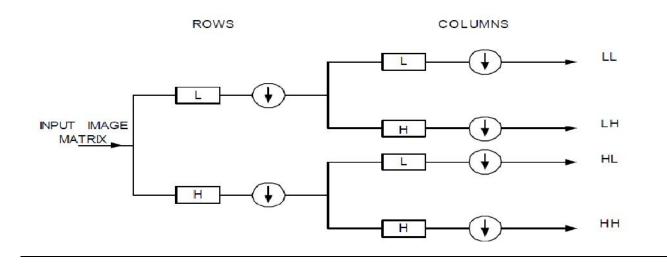


Figure (2.5) Wavelet decomposition for 2D Image

Each 2-D image can be classified as a grey scale image and that the corresponding grey scale value of anyimage is determined by using MATLAB. Therefore, the input two-dimensional array for this entire program would be the grey-scale value obtained. Once the coefficients are stored in the two-dimensional array, we first do the symmetric periodic extensions along the rows. This algorithm has been implemented using a bi-orthogonal filter due to its unique property of getting better reconstruction with the images. The input array obtained after symmetric periodic extension is then low-passed as well as high-passed

along each rows of the array. After completing the filtering operation along each of the rows, each of the row is then down sampled by a factor two which means every odd sample is eliminated from the array obtained after convolution Then we undergo the same process of filtering and convolution but on the columns this time.

2.7 Wavelet Reconstruction:

In practical, we often want to get its multi-stage reconstruction for a small wave, so that we can have a more accurate analysis of wavelet. Then we will introduce the multi-level of wavelet reconstruction specifically, we will introduce the multistage reconstruction diagram and multistage reconstruction algorithm, so that we can get more profound understanding from the multistage reconstruction of wavelet. In wavelet analysis, when a signal or graphics decomposition, we need restore it and know that if we can get the original signal or graphics. So we need introduce the wavelet multistage reconstruction.

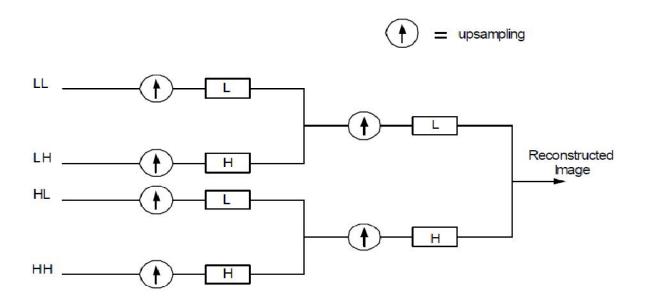


Figure (2.6) Wavelet Reconstruction for 2D Image

During the reconstruction part of the image, we apply the transforms on the columns first and then on the rows . Periodic symmetric extension is performed on all the four sub-bands obtained after the decomposition stage. The resultant array of all bands obtained after periodic extension are up sampled by a factor of two the reason being the coefficients were down sampled by the same factor 2 during decomposition. After up sampling by a factor 2, all the coefficients are zero padded followed by the low-pass and high-pass filtering. Same operations are iterated again but this time the transforms are applied on the rows to get the reconstructed image.

CHAPTER THREE

Literature Review

3.1 Literature Review

Literature presents with a copious number of researches for the noise removal in medical images. Several researches in the literature are based on.

The effect of various noise reduction filters on computed tomography (CT) images has been analysed by Lanzolla et al. (2009)[28].Based on the combination of Gaussian and Prewitt operators they have bestowed a denoising filter. Experimental values have proved that their presented technique has permitted to utilize low radiation dose protocol in CT examinations as well as enhanced the image quality. Their formulation was conceded out in combination with "G.Moscati" Hospital of Taranto (Italy) which presented all the images and technical materials engaged in the proposed algorithm.

Guangming Zhang et al. (2009) [29] have proposed an enhanced technique for CT medical image de-noising that bestowed autonomous component analysis and dynamic fuzzy theory. At first, a random matrix was formed to split the CT image for evaluation. Afterward, dynamic fuzzy theory was practicated to set up a sequence of adaptive membership functions to generate the weights degree of truth. At last, the weights degree was applied to optimize the value of matrix for image reconstruction. Following their model, helps the selection of matrix to be optimized scientifically and self-adaptively.

A wavelet based structure-preserving method was proposed by Borsdorf et al. (2008) [30] for noise reduction in CT images which could be utilized mutually with different reconstruction methods. Their technique was based on the deduction that the data may perhaps be decomposed into information and temporally uncorrelated noise. The investigation of correlations among the wavelet representations of the input images endowed isolating information from noise down to a definite signal-to-noise level.

Prof. Syed Amjad Ali, 2Dr. Srinivasan Vathsal and 3Dr. K. Lal kishore(2010) [31] proposed Denoising the CT images removes noise from the CT images and so makes the disease diagnosis procedure more efficient. The denoised images have a notable level of raise in its PSNR values, ensuring a smoother image for diagnosis purpose.

Wavelet coefficients with undersized correlation were minimized, at the same time those with high correlations were subjected to indicate structures and are conserved. The crucial noise-suppressed image was regenerated from the averaged and weighted wavelet coefficients of the input images. The magnitude as well as efficiency estimation on phantom and genuine clinical data adduced that high noise reduction rates of around 40% may perhaps be attained without substantial loss of image resolution.

Hybrid Iterative Reconstruction Technique was prposed by Seth Kligerman, MD(2013) [32] to To determine whether an iterative reconstruction (IR) technique (iDose, Philips Healthcare) can reduce image noise and improve image quality in obese patients undergoing computed tomographic pulmonary angiography (CTPA), their study suggests that the use of IR techniques can significantly reduce image noise and improve image quality in obese patients undergoing CTPA.

V.R.Vijaykumar, P.T.Vanathi, P.Kanagasabapathy(2014) [33], In this paper, a new fast and efficient algorithm capable in removing Gaussian noise with less computational complexity is presented. The algorithm initially estimates the amount of noise corruption from the noise corrupted image. In the second stage, the center pixel is replaced by the mean value of the some of the surrounding pixels based on a threshold value. Noise removing with edge preservation and computational complexity are two conflicting parameters. The proposed method is an optimum solution for these requirements. The performance of the algorithm is tested and compared with standard mean filter, wiener filter, alpha trimmed mean filter K- means filter, bilateral filter and recently proposed

trilateral filter. Experimental results show the superior performance of the proposed filtering algorithm compared to the other standard algorithms in terms of both subjective and objective evaluations. The proposed method removes Gaussian noise and the edges are better preserved with less computational complexity and this aspect makes it easy to implement in hardware.

Versha Rani1, Priyanka Kamboj (2013) [34]Their proposed method presents the results of Hybrid filter which is combination of the curvelet transformation, Unsharp Mask filter and Median Filter on to the images to observe the change in PSNR ratio and MSE ratio. The noisy images are simulated by adding Gaussian noise, salt and pepper noise, speckle noise and possion noise on the original images. The performance of the method is illustrated with both quantitative and qualitative performance measure. The qualitative measure is the visual Quality of the resulting image. The peak signal to noise ratio (PSNR) is used as quantitative measure. The resulting images after the filtering appear most effective and denoised than the previous noisy image.

J UMAMAHESWARI, Dr.G.RADHAMANI (2012) [35], there proposed a new technique based on the hybridization of wavelet filter and center weighted median filters is proposed for de-noising multiple noise (Gaussian and Impulse) images. The model is experimented on standard Digital Imaging and Communications in Medicine (DICOM) images and the performances are evaluated in terms of peak signal to noise ratio (PSNR), Mean Absolute Error (MAE), Universal Image Quality Index (UQI) and Evaluation Time (ET).

F. E. Ali et al. (2008) [36] have presented a curvelet based approach for the fusion of magnetic resonance (MR) and computed tomography (CT) images. The objective of the fusion of an MR image and a CT image of the same organ was to obtain a single image containing as much information as possible about that organ for diagnosis. Some attempts

made are proposed for the fusion of MR and CT images using the wavelet transform. Since medical images have several objects and curved shapes, it was expected that the curvelet transform would be better in their fusion. The simulation results show the superiority of the curvelet transform to the wavelet transform in the fusion of MR and CT images from both the visual quality and the peak signal to noise ratio (PSNR) points of view.

Chapter Four

Methodolog

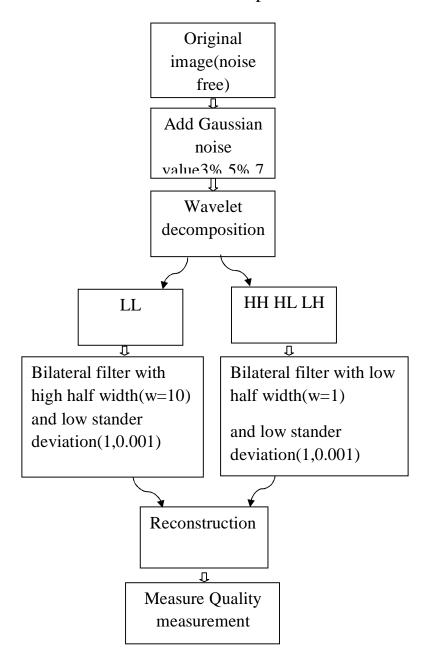
4.1 Methodology:

In the hybrid work, contains a comparative analysis of a number of de-noising algorithms namely wiener filtering, antistropic diffusion filtering, Bilateral filtering, median filtering, Wavelet filtering, Total variation filtering and convential antistropic diffusion filtering are combined to form a hybrid de-noising model. These techniques are used to suppress the noise (Gaussian noise). At the beginning image of ct scan were downloaded from(www.med,harvard.edu/aanlib/home.html)this image was introduced to media tool(mat lab). The image was read in mat lab and displayed, containing all its information (pixel information ,type ,size,color.....) ,the image was then converted from RGB to Gray. Gaussian noise was added to the image, the two images i.e. the image converted to RGB and the noisy image were subtracted to obtain the difference then a of filters were applied to the images. Certain parameters such as sequence MSE,RMSE,PSNR and SNR, were computed in order to be compared with the previous algorithms. After the comparison was done the results obtained showed that the Bilateral filter was the best compared to the other filters. To enhance the results obtained from the Bilateral filter a wavelet decomposition technique was applied.

The method steps are:

| Ш | Input image then add Gaussian noise with three different value 3%, 5%, 7% to three |
|---|--|
| | different image. |
| | Use wavelet decomposition to separate the lower part and the higher part of the |
| | signal spectrum. |
| | Use bilatral filter with specific parameters to denoise image. |
| | Finally reconstruct image and measure the quality of the output image. |

4.2 **Flow Chart**: show the method steps



Chapter Five

Results and Discussion

5.1 Results and Discussion:

This research contains the results obtained after following the wiener filtering, wavelet decomposition, Antistropic filtering, ,Bilateral filtering, median filtering ,Wavelet filtering, Total variation filtering and convential antistropic filtering. Then, some quantitative performance metrics like MSE, RMSE,PSNR, SNR, and The noise were computed and compared for 3different values of noise3%,5% and7%.

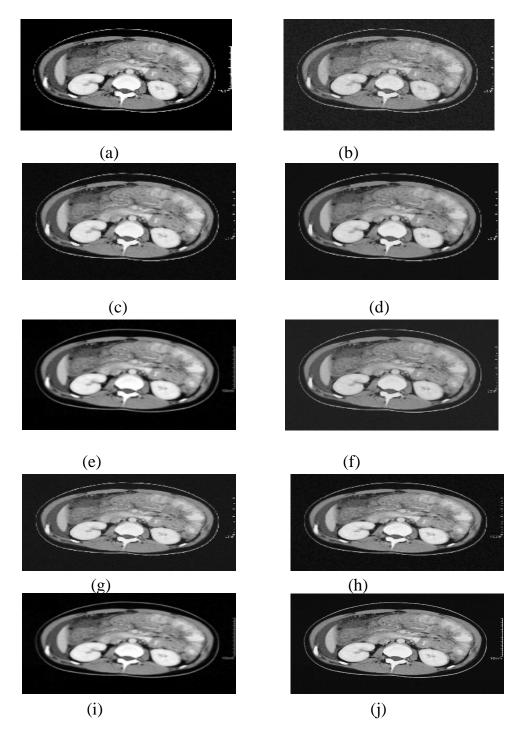


Figure (5.1)shows CT images (a) original image ,(b) noisy image with gaussian noise 3%,(c) image filtered by hyper median filter,(d) image filtered by antistropic filter,(e)image filtered by convential antistropic filter,(f) image filtered by wavelet filter,(g) image filtered by bilatral filter(h) image filtered by winner filter (i) image filtered by total variation filter, (j) image filtered by bilateral filter and wavelet decomposition.

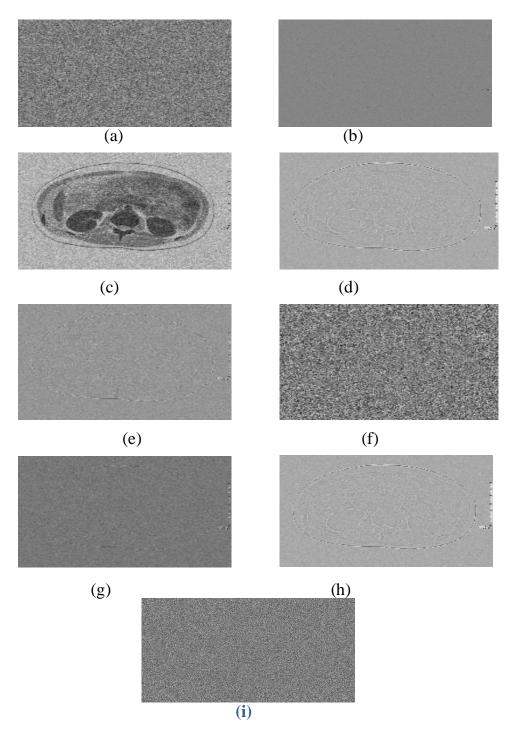


Figure (5.2)method noise images (a) 3% added noise ,(b) median filter noise ,(c) antistropic filter noise,(d) convential antistropic filter noise,(e) wavelet filter noise ,(f) bilatral filter,(g) winner filter noise (h) total variation filter noise,(i) proposed method noise result.

Table (5.1): shows the Quantitative Measurement of image interrupted by 3% Gaussian noise

| | MSE | RMSE | PSNR | SNR |
|------------------------|----------|--------|---------|---------|
| median filter | 0.000714 | 0.0267 | 79.6215 | 74.0972 |
| Antistropic diffusion | 0.0101 | 0.1007 | 68.1020 | 47.5642 |
| filter | | | | |
| Convential anisotropic | 0.0032 | 0.0304 | 73.5087 | 58.9892 |
| diffusion filter | | | | |
| wavelet filter | 0.0014 | 0.0380 | 76.5792 | 68.0168 |
| bilatral filter | 0.000387 | 0.0197 | 82.2910 | 80.2356 |
| wiener filter | 0.0017 | 0.0415 | 75.8136 | 65.3209 |
| total variation filter | 0.0049 | 0.0701 | 71.2481 | 54.8084 |
| | | | | |
| Proposed method | 0.000387 | 0.0197 | 82.2845 | 80.4965 |

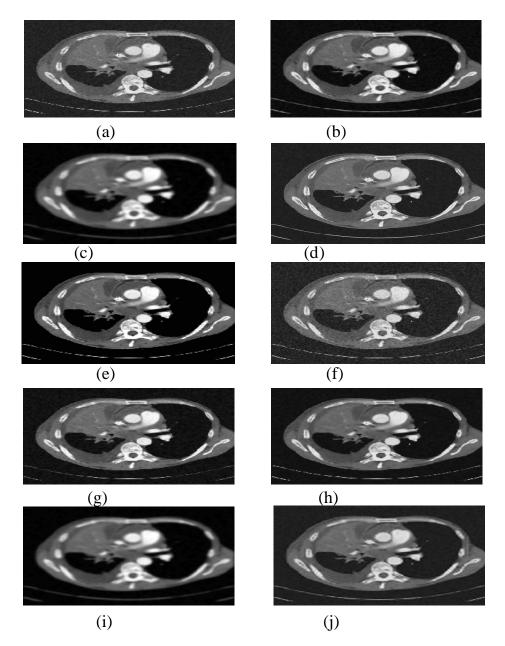


Figure (5.3)shows CT images (a) original image ,(b) noisy image with gaussian noise 5%,(c) image filtered by hyper median filter,(d) image filtered by antistropic filter,(e)image filtered by convential antistropic filter,(f) image filtered by wavelet filter,(g) image filtered by bilatral filter(h) image filtered by winner filter (i) image filtered by total variation filter,(j) image filtered by bilateral filter and wavelet decomposition.

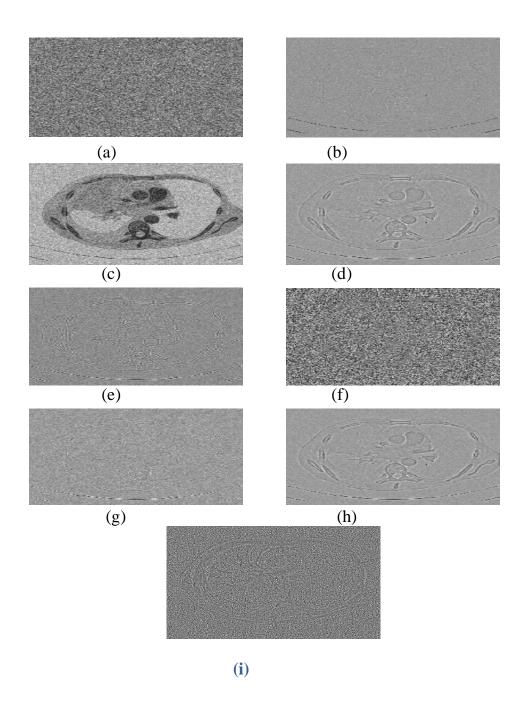


Figure (5.4)method noise (a) added noise ,(b) median filter noise ,(c) antistropic filter noise,(d) convential antistropic filter noise,(e) wavelet filter noise ,(f) bilatral filter,(g) winner filter noise (h) total variation filter noise,(i) proposed method noise result.

Table (5.2): shows the Quantitative Measurement of image interrupted by 5% Gaussian noise

| | MSE | RMSE | PSNR | SNR |
|------------------------|-----------|--------|---------|---------|
| median filter | 0.0023 | 0.0478 | 74.5694 | 64.4010 |
| Antistropic diffusion | 0.0171 | 0.1312 | 65.8032 | 43.7802 |
| filter | | | | |
| Convential anisotropic | 0.0081 | 0.0902 | 69.0631 | 51.7275 |
| diffusion filter | | | | |
| wavelet filter | 0.0048 | 0.0691 | 71.3742 | 56.9881 |
| bilatral filter | 0.0004352 | 0.0209 | 81.7738 | 80.5534 |
| wiener filter | 0.0040 | 0.0633 | 72.1361 | 58.7835 |
| total variation filter | 0.0116 | 0.1075 | 67.5377 | 48.2454 |
| | | | | |
| Proposed method | 0.0004347 | 0.0209 | 81.7827 | 81.2764 |

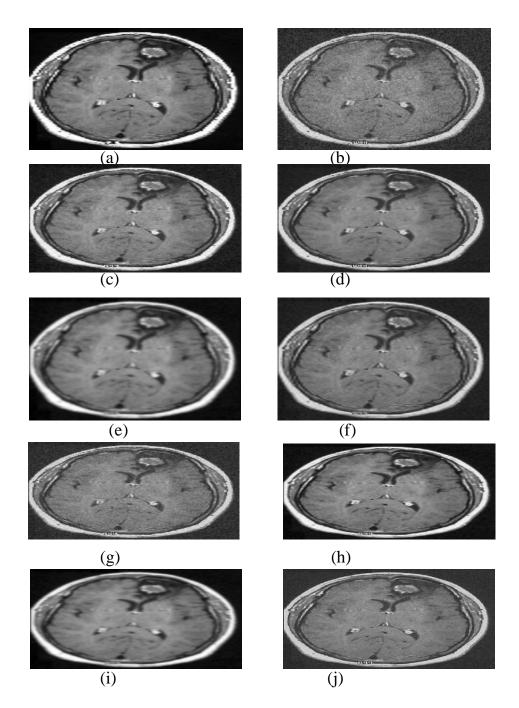


Figure (5.5)shows CT images (a) original image ,(b) noisy image with gaussian noise7%,(c) image filtered by hyper median filter,(d) image filtered by antistropic filter,(e)image filtered by convential antistropic filter,(f) image filtered by wavelet filter,(g) image filtered by bilatral filter(h) image filtered by winner filter (i) image filtered by total variation filter,(j) image filtered by bilateral filter and wavelet decomposition.

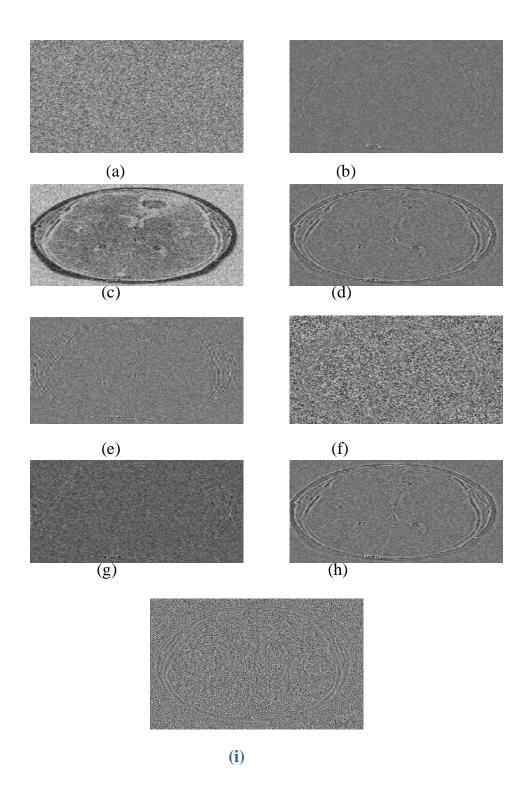


Figure (5.6)shows noise (a) added noise, (b) median filter noise, (c) antistropic filter noise, (d) convential antistropic filter noise, (e) wavelet filter noise, (f) bilatral filter, (g) winner filter noise (h) total variation filter noise, (i) proposed method noise result.

Table (5.3): shows the Quantitative Measurement of image interrupted by 7% Gaussian noise

| | MSE | RMSE | PSNR | SNR |
|------------------------|----------|--------|---------|---------|
| median filter | 0.0033 | 0.0571 | 73.0395 | 61.4606 |
| Antistropic diffusion | 0.0156 | 0.1251 | 56.2206 | 45.7594 |
| filter | | | | |
| Convential anisotropic | 0.0106 | 0.1029 | 67.9168 | 49.6650 |
| diffusion filter | | | | |
| wavelet filter | 0.0073 | 0.0852 | 69.5610 | 53.5411 |
| bilatral filter | 0.000328 | 0.0181 | 83.0067 | 84.4109 |
| wiener filter | 0.0062 | 0.0785 | 70.2623 | 55.0659 |
| total variation filter | 0.0159 | 0.1259 | 66.1645 | 45.6303 |
| | | | | |
| Proposed method | 0.000327 | 0.0181 | 83.0191 | 85.2935 |
| = P 00000 111001100 | 0.000021 | 0.0101 | 00.0171 | 00.2700 |

Discussion:

The performance of various filters: a wiener filtering, Bilateral filtering, median filtering ,Wavelet filtering, Total variation filtering and antistropic filtering are studied under 7% Gaussian noise conditions .From Tables(5.1), (5.2), (5.3), it is observed that the Bilateral filtering, median filtering are better in terms of MSE,SNR and PSNR.

For proper judgment of performance of filters, the subjective evaluation should be taken into consideration. The filtering performances of various filters on ct images are shown in the figures: (5.1) (5.3), (5.5), From these figures, it is observed that the edges of the images filtered using bilateral filter have been maintained and the blurring was eliminated, images filtered using total variation filter have been smoother inside but with jumps across the boundaries. Images filtered using anisotropic filters became smoother in the flat regions and the edge have been preserved. The edges of the images filtered by median filter have been preserved and the noise has been removed. The coefficients of the images are attenuated by wavelet transforming order to reduce the noise.

From figure (5.2) (5.4), (5.6), its observe by the pattern of noise showed by subtracting each filter image from 3%,5% and 7% reverence noisy images, that the bilateral filter noise pattern is the closest one to the reverenced pattern, antistropic filters and total variantion filter noise pattern conclude some edge and details of the image.

From the previous results we conclude that the bilateral filter gave better results compared to other filters, the total variation filter gave a blurred image with less detail, while the wavelet filter gave some details but still small amount of blurring was observed, also that by rising the noise value the bilateral filter give better results in SNR value and the convential antistropic filters gave a blurred image with less detail.

For the proposed method the results of the metrics showed much better results than the bilateral filter alone.

Chapter Six

Conclusions and Recomendation.

6.1 Conclusions:

The proposed method presents the results of Hybrid filter which is combination of the wavelet decomposition and bilateral Filter on to the images to observe the change in MSE,RMSE,PSNR ratio and SNR ratio.

The noisy images are simulated by adding Gaussian noise on the original images. The performance of the method is illustrated with both quantitative and qualitative performance measure. The qualitative measure is the method noisefrom images substraction and the visual Quality of the resulting image. The MSE,RMSE,PSNR and SNR are used as quantitative measures.

The SNR value became much better as the value of noise arises.

The resulting images after the filtering appear most effective and denoised than the previous noisy image.

6.2 Recommendation

- -Other new transformation can be used such as contorlet.
- -The neural network can be used.
- -adding different type of noise.
- -using different type of filters.

REFERENCE:

- [1] S. Senthilraja, Dr. P. Suresh, Dr. M. Suganthi. Noise Reduction in Computed Tomography Image Using WB Filter.
- [2] Versha Rani1, Priyanka Kamboj2.Image Enhancement using Hybrid Filtering Technique
- [3] R. Sivakumar, 2007.De-noising Of Computer Tomography Images Using Curve let Transform. "ARPN Journal of Engineering and Applied Sciences. Vol. 2, No. 1, pp. 21-26.
- [4] G. Landi an E. Loli Piccolomini, , 2009. An Algorithm for Image De-noising with Automatic Noise Estimate . Journal of Mathematical Imaging and Vision, Vol. 34, No. 1, pp. 98–106.
- [5] Akshaya. K. Mishra, Alexander Wong, David. A. Clausi and Paul. W. Fieguth, December 2008. Adaptive nonlinear image de-noising and restoration using a cooperative Bayesian estimation approach in proceedings of the Sixth Indian Conference on Computer Vision, Graphics & Image Processing, pp. 621-627.
- [6] Micheal F. McNitt-gray. Tradeoffs in CT Image Quality and Dose. the C.V. Mosby Company London.
- [7] Computed Tomography Scientific/Technological fact sheet.
- [8] Haryana. Seth Jai Parkash Mukand Lal Institute Radaur .Student of Department of Computer Science and Application, department of Radiology Palo Alto Medical Clinic 795 El Camino Real, Palo Alto, CA 94301 (650) 853-2957
- [9] www.nhs.uk/conditions/ct-scan/.../Introduction.as..National Health Serviceby NHS Choices 2011.
- [10] Kenneth M. Hanson , Noise and computed contrast discrimination in tomography
- [11] The Scientist and Engineer's Guide to Digital Signal Processing.
- [12] www.ni.com.Peak Signal-to-Noise Ratio as an Image Quality MetricPublish Date: Sep., 2013.
- [13] JOHN L. SEMMLOW.Biosignal and Biomedical Image Processing MATLA B-Based Application.s
- [14] Image Registration for Area Matching by Using Transform Based Methods.
- [15] Rafael C .Gonzalez and Richard EWood , 2002. digital image processing.second edition, publisher Tom Robbins.
- [16] Sobika Ambardar, Manish Singhal, 2008.A Review and Comparative Study of De-noising Filters in Ultrasound Imaging. International Journal of Emerging Technology and Advanced Engineering Website: www.ijetae.com.

- [17] Christos P. Loizoua,b,*, Charoula Theofanousb, Marios Pantziarisc, Takis Kasparisb, 2 0 1 4. Despeckle filtering software toolbox for ultrasound imaging of the common carotid artery,computer methods and programs in biomedicin, 109–124.
- [18] P. Perona and J. Malik. Scale-space and edge detection using anisotropic diffusion.IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 12, no. 7.
- [19] nuha ,hybrid technique for noise removal from CTimage
- [20] Zeinab A.Mustafa, Yasser M.Kadah, Multi Resolution Bilateral Filter for MR Image Denoising.
- [21] Durand, F., Dorsey2002. Fast bilateral filtering for the display of high-dynamic-range images. SIGGRAPH.
- [22] Porikli, F. 2008. Constant time bilateral filtering.
- [23]Petschnigg, G., Agrawala, M., Hoppe, H., Szeliski, R., Cohen, M., Toyama, K ,2004.Digital photography with flash and no-flash image pairs,SIGGRAPH.
- [24] Bae, S., Paris, S., Durand, F. 2006. Two-scale tone management for photographic look SIGGRAPH.
- [25] Paris, S., Durand, 2006.A fast approximation of the bilateral filter using a signal processing approach. ECCV.
- [26] Yang, Q., Tan, K.H., Ahuja, 2009. Real-time bilateral filtering.
- [27] Guangzhou, P. R. China, July 2010. The Wavelet Decomposition And Reconstruction Based on The Matlab. Proceedings of the Third International Symposium on Electronic Commerce and Security Workshops (ISECS '10), 29-31, pp. 143-145.
- [28] Lanzolla, Andria, Attivissimo, Cavone, Spadavecchia and Magli, 2009. Denoising filter to improve the quality of CT images. in proceedings of IEEE Conference on Instrumentation and Measurement Technology, pp.947-950.
- [29] Guangming Zhang, Xuefeng Xian, Zhiming Cui and Jian Wu, 2009. Medical Image De-noising Extended Model Based on Independent Component Analysis and Dynamic Fuzzy Function. in proceedings of the IEEE International Conference on Information Engineering, Vol. 1, pp.209-212.
- [30] A. Borsdorf, R. Raupach, T. Flohr and J. Hornegger, 2008. Wavelet Based Noise Reduction in CT-Images Using Correlation Analysis." IEEE Transactions on Medical Imaging, Vol. 27, No.12, pp. 1685-1703.
- [31] 1Prof. Syed Amjad Ali, 2Dr. Srinivasan Vathsal and 3Dr. K. Lal kishore, July 2010. CT Image Denoising Technique using GA aided Window-based Multiwavelet Transformation and Thresholding with

the Incorporation of an Effective Quality Enhancement Method.International Journal of Digital Content Technology and its Applications Volume 4, Number 4.

[32] Kligerman, MD,* Dhruv Mehta, MS,w Mahmmoudreza Farnadesh, MD,* Jean Jeudy, MD,* Kathryn Olsen, MD,* and Charles White, MD*, January 2013.Use of a Hybrid Iterative Reconstruction Technique to Reduce Image Noise and Improve Image Quality in Obese Patients Undergoing Computed Seth Thorac Imaging _ Volume 28, Number 1. Tomographic .Pulmonary Angiography [33] V.R.Vijaykumar, P.T.Vanathi, P.Kanagasabapathy, February 2014. Fast and Efficient Algorithm to Remove Gaussian Noise in Digital Images. [34] Versha Rani1, Priyanka Kamboj2, 1990.Image Enhancement using Hybrid Filtering Technique, Volume 2 6, 2013www.ijsr.netpp. Issue June [35]J,UMAMAHESWARI, Dr.G.RADHAMANI 2012. Hybrid De-noising Method for Removal of Mixed Noise in Medical Images, Vol. 3, No. 5.

[36] F. E. Ali, I. M. El-Dokany, A. A. Saad and F. E. Abd El-Samie, 2008. Curvelet Fusion of MR and CT Images. Progress In Electromagnetics Research C, Vol. 3, pp; 215–224.