NOISE REDUCTION IN MRI IMAGES

Thesis submitted in partial fulfillment of the requirement for the award of degree of

Master of Engineering

in

Electronic Instrumentation and Control

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DECLARATION

The thesis submitted here is a study on noise reduction in MRI images. I hereby declare that the report entitled "Noise Reduction In MRI Images" is an authentic record of my own work carried out as requirements for the award of degree of M.E. (Electronic Instrumentation & Control) at Thapar University, Patiala, under the supervision of Mr. Mandeep Singh, Assistant Professor and Mr. M.D. Singh, Lecturer, EIED dept., Thapar University, Patiala during January to June 2008.

(Bharti Sharma)

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It is certified that the above statement made by the student is correct to the best of our knowledge and belief.

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ABSTRACT

Real world signals usually contain departures from the ideal signal that would be produced by our model of the signal production process. Such departures are referred to as noise. Noise arises as a result of unmodelled processes going on in the production and capture of the real signal. It is not part of the ideal signal and may be caused by a wide range of sources, *e.g.* variations in the detector sensitivity, environmental variations, the discrete nature of radiation, transmission or quantization errors, *etc.* It is also possible to treat irrelevant scene details as if they are image noise. The characteristics of noise depend on its source, as does the operator which best reduces its effects.

In this study, we have tried to analyze the different types of noises present in MRI images and to filter these noises using different digital filters. In the given figure, we added poisson, salt & pepper, speckle, Gaussian, additive Gaussian and multiplicative Gaussian noise. In the present study, we quantitatively establish the use of various parameters which helps in analysing the filter performance that are otherwise difficult to determine by other classical methods of image processing.

This study investigates which type of filter removes or reduces which noise properly and if combination of filters are used then which type of filters give the desired results. The present study focuses on max, min, median, cumulative mean, bilateral and Gaussian filter. The parameters which determine the filter performance are PSNR, WPSNR, Correlation, SNR.

ORGANIZATION OF THESIS

The first chapter is the introduction to digital image processing and focuses on basic characteristics of image. The second chapter is based on image noise, in which the concept of image noise is briefed and various types of noise are discussed. The next chapter deals with the magnetic resonance imaging process in detail. The fourth chapter is based on noise filtering and various filters are discussed. The next chapter is based on the methodology used in this work. It basically gives the method used to complete this work. The last chapter concludes with the results and the conclusion with the future scope of the work.

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LIST OF ABBREVIATIONS

MRI – Magnetic Resonance Imaging

MIC – Morphological Image Cleaning

CNR – Contrast-to-noise Ratio

TF – Trilateral Filtering

BF- Bilateral Filtering

DSA – Digital Subtraction Angiography

MAE – Mean Absolute Error

PSNR – Peak Signal to Noise Ratio

PDF – Probability Density Function

CYMK – Cyan Yellow Magenta black

SNR – Signal-to-Noise Ratio

AWGN – Additive White Gaussian Noise

DNR – Dynamic Noise Reduction

NMR – Nuclear Magnetic Resonance

EPI – Echo Planar Imaging

FOV – Field Of View

NEX – Number of acquisitions

ROI – Region Of Interest

MATLAB – MATrix LABoratory

WPSNR – Weighted Peak Signal-to-Noise Ratio

LITERATURE SURVEY

In 1994, Mark Allen Schulze, presented, the use of morphology-based nonlinear filters to enhance biomedical images. Specifically, new filters based on mathematical morphology were developed, analyzed, and applied to a variety of medical images. The behavior of the standard morphological filters was undesirable for certain applications, and the new filters were designed to overcome these weaknesses. Some new analysis techniques were introduced, including a method to quantify the response of filters to two-dimensional features. These new analysis methods and the basic statistical and deterministic analyses were used to compare the new filters with the standard filters. Finally, the new nonlinear filters were used to enhance magnetic resonance, thermographic, and ultrasound images and their performance was compared to established filtering techniques for each of the imaging modalities. [Mark Allen Schulze, 1994]

In 1995, Richard Alan Peters II presented the description and analysis of a new morphological image cleaning algorithm (MIC) that preserves thin features while removing noise. MIC was useful for greyscale images corrupted by dense, low-amplitude, random or patterned noise. Such noise was typical of scanned or still-video images. MIC differed from previous morphological noise filters in that it manipulates residual images – the differences between the original image and morphologically smoothed versions. It calculated residuals on a number of different scales via a morphological size distribution. It discards regions in the various residuals that it judges to contain noise. MIC created a cleaned image by recombining the processed residual images with a smoothed version. [Peters R, 1995]

In 1998, Shanon proposed an objective measure of MR image quality. This measure took into account the contrast-to-noise ratio (CNR), scan resolution, and field of view. It was used to derive an optimum in the tradeoff problem between image resolution and CNR, and as a criterion to assess the usefulness of high-resolution (512') MR images. The result told that, for a given total acquisition time, an optimum value of the resolution can be found. This optimum was very broad. To apply Shannon's theory on information content to MR images, a model for the spatial spectral power density of these images was required. Such a model have been derived from experimental observations of ordinary MR images, as well as from theoretical considerations. The MR imaging problem, the trade off between pixel size and contrast-to-noise ratio, can be explicitly solved. The information content criterion have been shown to be both applicable and useful as an image quality criterion for MR. It was known that this criterion also matched the subjective evaluations of images. [Shanon, 1998]

In 1999, M.Lendl et. al. presented a novel algorithm for estimating the noise variance of an image. The image was assumed to be corrupted by Gaussian distributed noise. The algorithm estimated the noise variance in three steps. At first the noisy image was filtered by a horizontal and a vertical difference operator to suppress the influence of the (unknown) original image. In a second step a histogram of local signal variances was computed. Finally a statistical evaluation of the histogram provided the desired estimation value. For a comparison with several previously published estimation methods an ensemble of 128 natural and artificial test images was used. It was shown that with the novel algorithm more accurate results can be achieved. The algorithm was based on an iterative histogram analysis with the aid of a cosine fade-out function. The entries of the histogram were the local noise standard deviations, whereas the image have been .prefiltered by difference operators in the vertical and horizontal directions. A rough comparison with several previously published estimation methods indicated an improved accuracy of the new algorithm with respect to the other methods. [Lendl M et. al., 1999]

In 1999, J. Sijbers et. al. presented Yang's version of the adaptive, anisotropic diffusion filter which was adopted and modified for the filtering of magnitude MR data. In the past, many efforts were devoted to the reduction of noise, or equivalently, the estimation of the underlying, noiseless signal. At present, the most common noise reduction technique is still time averaging. It had the major advantage that the signal-to-noise ratio (SNR) is increased while the spatial resolution remains intact, provided the imaging process was stationary. Since this approach was quite time consuming and hence not feasible in case of conventional 3D MR imaging, time averaging was usually replaced by spatial averaging. Filters applied to magnitude MR data should incorporate the probability density function that characterizes these data. In addition to good noise filtering performance, spatial resolution was retained due to the adaptive and anisotropic characteristics of the filter. [Sijbers J, 1999]

In 2000, Andreas Wrangsio presented a framework for denoising by first examining what the problem really is. What is a signal? What is noise? What is to be removed? A method based on Bayesian analysis was presented for denoising. The method was evaluated in theory and was practised on artificial and real data and a number of applications incorporating the proposed method were discussed. The field of medical image analysis is given special emphasis in the form of a chapter devoted purely to medical image denoising with example applications in MRI, ultrasound and digital X-ray imaging. The result was a method to reduce spatially uncorrelated noise in two- and three dimensional images making explicit use of available knowledge on the noise statistics. The method used very few and intuitive parameters. The parameters were easy to choose either as standard values or by simple estimation schemes. A framework for image denoising based on prior knowledge (or good guesses) on the noise statistics have been presented. The performance of the proposed methods have been analysed and a number of practical experiments with artificial as well as real data have been presented. The importance of noise reduction have been motivated by incorporating denoising as a preprocessing step to image segmentation and registration. The framework had also been applied to the art of image enhancement, where it was shown that it could be used to enhance lines and edges and to improve local contrast in images with a large dynamic range. Efficient implementation of the proposed techniques have been discussed and it have been shown how the methods can be simplified and applied to fairly time critical problems, at least for signals distorted by Gaussian noise. Finally, the framework have been applied to the field of medical image analysis. The issue of denoising as a preprocessing step to segmentation was once again emphasised. [Wrangsio A, 2000]

In 2001, Mukesh C.Motwani presented a review of some significant work in the area of image denoising. He had introduced some popular approaches, which were classified into different groups and an overview of various algorithms and analysis is provided. Insights and potential future trends in the area of denoising were also discussed.. This paper described 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. [Mukesh C, 2001]

In 2001, V. Musoko et. al. presented basic principles of median filtering on two and three dimensional biomedical images. The proposed algorithm of image de-noising was applied to magnetic resonance (MR) images. Results of such a non-linear filtering were compared with that achieved by linear filtering methods. Algorithms were at first verified for simulated images and then applied to real MR images. Median filtering is a a non-linear method used for the removal of impulsive noise. It was implemented to an image using a mask of odd length, the mask moved over the image and at each center pixel the median value of the data within the window was taken as the output. They had discussed the application of 2D and 3D median filter masks in the de-noising of MR images. Median filtering is very simple in operation, effective in filtering isolated impulses and has good edge preserving properties. Non-linear filters were applied to enhance MR images corrupted with impulsive noise. In this paper they proposed both the algorithms of 2D and 3D median filtering, even though their algorithms were simple and easy to implement they gave good efficiency in suppressing the impulsive noise. However it must be noted that a 3D median filter produced a smoother image appearance compared to the 2D median filter when processed noisy image sequence slices. [Musoko V and Proch A, 2001]

In 2004, Somkait Udomhunsakul proposed a feature extraction approach in medical magnetic resonance imaging (MRI). In this approach, first the combination of spatial filters using the 5x5 wiener filter followed by a 3x3 Gaussian filter were used to remove the noisy pixels while preserving the important information. Next, the edge detection algorithm based on multiple-scales cdge detection of Gabor filters was applied. Moreover, Wavelet transform based image fusion was used to combine the detail coefficients. Finally, the nonmaxima suppression technique was adopted to gct the final result. The experiments showed that the proposed algorithm can be detected well-localized, and thin edges. Therefore, the algorithm lead to a useful method for feature extraction in MRI images and can be used for diagnostic purposes. In this work, an integration method of noise suppression and edge detection in medical MRI images using multi-scales Gabor filters was presented and tested. The results revealed that the proposed approach compared with traditional methods (Laplacian, Laplacian of Gaussian and Sobel operator) can be detected well-localized, and thin edges. It can generate correct edges and rcmove the spurious edges due to noise. It also provided a clean edge map. Therefore, the proposed approach lead to a useful method for feature extraction in medical MRI images and can be used for diagnostic purposes. Also, the method was general and can be applied to other images. [Udomhunsakul S and Wongsita P, 2004]

In 2004, Pierre Gravel had developed a method to study the statistical properties of the noise found in various medical images. The method was specifically designed for types of noise with uncorrelated fluctuations. Such signal fluctuations generally originated in the physical processes of imaging rather than in the tissue textures. Various types of noise (e.g., photon, electronics, and quantization) often contribute to degrade medical images; the overall noise is generally assumed to be additive with a zero-mean, constant-variance Gaussian distribution. However, statistical analysis suggested that the noise variance could be better modeled by a nonlinear function of the image intensity depending on external parameters related to the image acquisition protocol. He presented a method to extract the relationship between an image intensity and the noise variance and to evaluate the corresponding parameters. The method was applied successfully to magnetic resonance images with different acquisition sequences and to several types of X-ray images. The method performed best on raw or unprocessed (and uncompressed) images. Such images awere usually modified by an operator to enhance their contrast and their edges, to smooth out the noise or to deblur the images. [Gravel P et. al., 2004]

In 2004, Wilbur C.K. Wonga et. al. presented a novel non-linear filtering method for medical images, namely trilateral filtering (TF). Their method, which worked along similar lines to bilateral filtering (BF), integrated geometric, photometric and local structural similarities to achieve edge-preserving smoothing. The method was simple to implement and was applicable to multi-dimensional signals. It only used a narrow spatial window (3 pixels in each dimension) and just took a single iteration in the smoothing process (i.e. the method is non-iterative). The experiments on digital subtraction angiography (DSA) and MRI had shown that the new filtering technique TF was capable of reducing noise (even severe noise) in medical images. Post-processing tasks, for instance, segmentation and feature extraction on the filtered images, had demonstrated the competence of TF in improving the quality of segmentation and in facilitating the feature extraction process. In order to evaluate the performance of the trilateral filter, they had conducted several experiments on 2D and 3D medical images. The experimental results had shown that this novel method was capable of producing greater noise reduction and smoothened the images without over-smoothing the edges, as compared to other edge-preserving noise reduction methods and the Gaussian filter. [Wilbur C and Albert C, 2004]

In 2006, Krishnan Nallaperumal proposed an improved and efficient adaptive median filter for salt & pepper impulse noise removal from digital images. The more perfect and computationally efficient filtering scheme had taken care to restore only the impulse corrupted pixels by a perfect mid-ranking image statistic from an approriate local neighbourhood while keeping the signal content of the uncorrupted pixels as such. The corrupted signals were identified by an adaptive technique and the signal loss due to misinterpretation of uncorrupted signals as corrupted was almost avoided to sustain the imagedetails intact. Experimental results showed that the proposed algorithm which detected impulses and restores the corrupted signals in a single efficient stretch was far more superior than many of the other median filters in terms of retaining the fidelity of the images corrupted by salt & pepper impulse noise even to the tune of ninety five percent. The objectiveness of the proposed filter in terms of Peak Signal to Noise Ratio and Mean Absolute Error at all noise levels showed the significance of this filter. [Nallaperumal K, 2006]

In 2007, J.V. Manjon presented an extension of a recently proposed filter to reduce random noise in multispectral MR images and tested it on synthetic and real images. He compared performance to a multispectral approach based upon the imaging physic. Clinical MRI data is normally corrupted by random noise from the measurement process which reduces the accuracy and reliability of any automatic analysis. For this reason, de-noising methods were often applied to increase the SNR and improve image quality. Most of these methods worked on single channel images by correcting each grey level using an implicit model of the surrounding region, but without taking into consideration the potential multispectral nature of MR images.They had explained how, for a noise filter to be statistically valid, its algorithmic form should be consistent with the statistical distributions present in real data. [Manjon J et. al., 2007]

In 2007, Amit Shrivastava et. al. had developed a method to detect the different types of noise in medical images and shows the effect of exponential distribution on the noise by evaluated the Probability density function (PDF) for the medical images. The results were analyzed compared with standard pattern of noise and evaluated through the quality metrics like mean and standard derivations. Medical imaging refers to technique and process used to create images of human body (or part thereof) for clinical purpose (medical procedures seeking to reveal diagnose or examine diseases) or medical science (including the study of normal anatomy and function) .Image processing techniques in medical imaging are used to analyze the symptoms of the patients with ease. Medical images often consist of random noise and which are affected during acquisition and it spread over the image. In such situation it is very difficult to diagnosis the particular disease. Therefore it is necessary to remove the noise from the image. Real images are often degraded by noise and this noise can occur during image transmission and digitization. In this work different medical images like MRI, MRI Brain have been studied for detecting various types of noises. The various types of noise like Gaussian, Salt & pepper and Poisson noise have been tested to detect and they had calculated the Probability Density Function for the Exponential Distribution in the noisy image. The result were analyzed and compared with the standard pattern of noises and were also evaluated through the Coefficient of Variation for the different noisy image. Through this work it was observed that the the PDF for different noise are same but the CV is Consistence for the Gaussian Noise. [Shrivastava A et.al., 2007]

CHAPTER 1
INTRODUCTION

1.1 Digital image processing

Many of the techniques of digital image processing, or digital picture processing as it was often called, were developed in the 1960s at the Jet Propulsion Laboratory, MIT, Bell Labs, University of Maryland, and a few other places, with application to satellite imagery, wirephoto standards conversion, medical imaging, videophone, character recognition, and photo enhancement. But the cost of processing was fairly high with the computing equipment of that era. In the 1970s, digital image processing proliferated, when cheaper computers and dedicated hardware became available. Images could then be processed in real time, for some dedicated problems such as television standards conversion. As general-purpose computers became faster, they started to take over the role of dedicated hardware for all but the most specialized and compute-intensive operations.

With the fast computers and signal processors available in the 2000s, digital image processing has become the most common form of image processing, and is generally used because it is not only the most versatile method, but also the cheapest.

In today's world of advanced technology where most remote sensing data are recorded in digital format, virtually all image interpretation and analysis involves some element of digital processing. Digital image processing may involve numerous procedures including formatting and correcting of the data, digital enhancement to facilitate better visual interpretation, or even automated classification of targets and features entirely by computer. In order to process remote sensing imagery digitally, the data must be recorded and available in a digital form suitable for storage on a computer tape or disk. Obviously, the other requirement for digital image processing is a computer system, sometimes referred to as an image analysis system, with the appropriate hardware and software to process the data. Several commercially available software systems have been developed specifically for remote sensing image processing and analysis.

Digital image processing is a subset of the electronic domain wherein the image is converted to an array of small integers, called pixels, representing a physical quantity such as scene radiance, stored in a digital memory, and processed by computer or other digital hardware. Digital image processing, either as enhancement for human observers or performing autonomous analysis, offers advantages in cost, speed, and flexibility, and with the rapidly falling price and rising performance of personal computers it has become the dominant method in use. [http: dip]

1.2 Image Basics

This describes the basic image characteristics images can have. These include:

1.2.1 Image metrics

1.2.2 Image modes

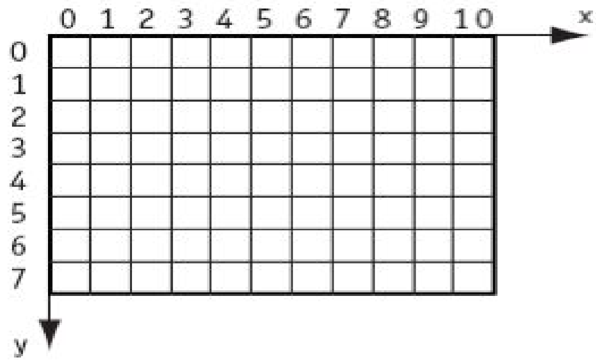
1.2.3 Mean value and deviation

1.2.4 Image histograms

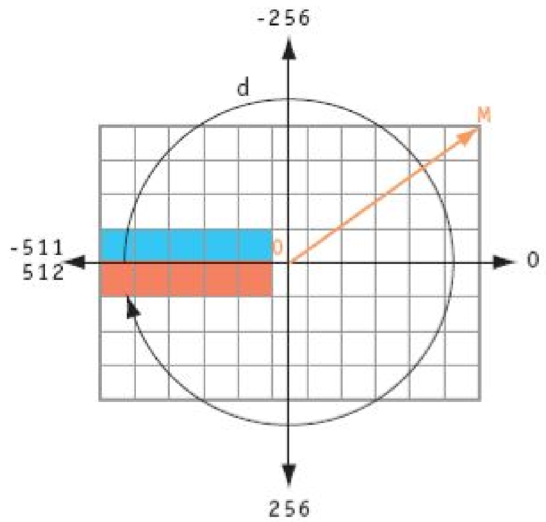
1.2.5 Digital processing of camera images

1.2.1 Image metrics

Images are built up of pixels that contain color information and are aligned with the cartesian coordinate system.The zero point is found at the top-left corner of the image (in PostScript, for example, the zero point is found at the bottom-left corner of the page).The image's width is represented by the variable X,the image's height with the variable Y.Figure 2.1a shows the coordinates of an image with the width and height of 11 × 8 pixels.The zero point in polar coordinates is found at the middle of the image.The two coordinate axes are the angle (or direction) and magnitude (or distance from the image's center) and are represented by the variables d and m, respecitvely.Figure 1.1b shows the computed polar coordinates of the same image.



(a)



(b)

FIG 1.1: Visualization of x,y,d,m variables and X,Y,M pseudo constants

1.2.2 Image Modes (color models)

When working with pixel-based images,one can work with either black-and-white (bitmap), greyscale and colored images.You have to understand that the pixel information between these image modes is different. This also plays a part in the image file's size and memory size needed.

a) Bitmap images

Bitmaps are black-and-white images, whose pixel information can only be black or white and nothing in between. One bit can have the information 0 (Black) or 1

(White) and nothing else, and that is enough to describe one pixel in a bitmap. The memory requirements for a 640 × 480 bitmap is 37.5 KB.

b) Grayscale images

In Grayscale images, a pixel is described by one byte or 8 bits. The image consists of eight bit planes in one channel. You can combine the 8 bits in up to 256 combinations.So a pixel can, for example,have the following values: 0 (black), 64 (dark gray), 128 (gray), 192 (light gray) and 255 (white).

The memory requirements for a 640 × 480 Grayscale image is 300 KB.

c) RGB images

Televisions, computer monitors, scanners and our eyes work with the emission respectively the absorption of Red, Green and Blue light rays. The combination of these three colors in different intensities can produce millions of different colors. These colors are actually light rays which have a certain frequency or wavelength. Imagine figure 1.2 as if one were in a dark room and were projecting three colored lamps onto the wall. When mixed together, the frequencies are added together.This is the additive color mixture.

If you further imagine that each lamp can be set to 256 intensity settings, you could mix up to 256 × 256 × 256 = 16.7 million colors. Each color (red, green and blue) – in Photoshop called channels – is described thus in 8 bits or one byte. One pixel in your RGB-image is described by 3 × 8 bits = 24 bits. The memory requirements for a 640 x 480 RGB image are 900 KB.

FIG 1.2: Projections of three lamps with the colors red,green and blue onto a wall in a dark room

A gray tone can be achieved by setting equal intensities of the three color channels:

(0, 0, 0) black

(128, 128, 128) gray

(192, 192, 192) light gray

(255, 255, 255) white

RGB images are mostly used for web graphic creation,presentations in general and CD-ROM productions. Currently,FilterMeister supports only RGB images, so most of the plug-ins or filters in this paper are suitable for RGB images only.

d) CMYK Images

These images are used specially for print products such as booklets, magazines, catalogs, etc.Most CMYK images are converted after scanning (with the scanner's driver) or when converting images with other color spaces to CMYK.CMYK stands for the inks Cyan (blue),Magenta (pinkish),Yellow and Black. These colors are printed on media and are not emitted colors (such as from the monitor).Thus, light is absorbed from the ink on paper and our eyes see only the reflected light rays (see figure 1.3).

Therefore,when nothing is printed, you see the media's color, which in most cases is the paper white.When you print Cyan with Magenta, you'll get a purplish

Blue,Magenta with Yellow gets you Red and Yellow with Blue obviously Green.And when all colors are mixed together, all light rays are absorbed and you see a black area on the white paper. Since the pixel intensity in each channel is still eight bits or one byte, each CMYK pixel is described by 32 bits.The memory requirements for a 640 x 480 CMYK image is 1200 KB or 1.2 MB. [http: image formats]

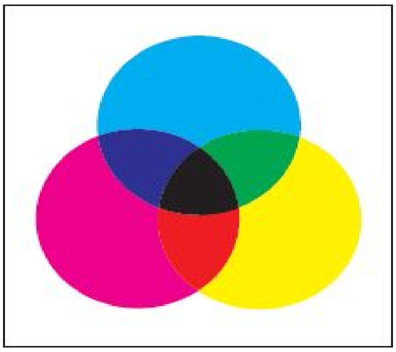


FIG 1.3: A print of three colored circles(cyan,magenta and yellow) on paper

1.2.3 Mean value and Deviation

The two image characteristics mean value and deviation are often needed for digital processing tasks or for statistical reasons. The mean value mz of the channel z states if the channel is darker or lighter in the whole.A greyscale image with m=170, for example, is identified to be lighter.An RGB image having a red channel mean value of mR=87, a green channel mean value of mG=110 and a blue channel mean value of mB=77 is seen as a dark green image (for example an image of a tree landscape).Note that the mean value cannot state if the image is contrasty or not – when, for example,one image contains the gray tone 128 and the other image contains a checkerboard pattern consisting of the two gray tones 0 and 255, the same mean value of m=127.5 is returned.

$$m = \frac{1}{X \times Y} \sum_{x=0}^{X-1} \sum_{y=0}^{Y-1} src(x, y, z)$$

The deviation qz returns the contrast value of the current channel z.Lower values specify that an image is in low contrast (flat) while high values specify that an image is high in contrast (contrasty).

$$m = \frac{1}{X \times Y} \sum_{x=0}^{X-1} \sum_{y=0}^{Y-1} (src(x, y, z) - m)^2$$

(a) **(b)**

FIG 1.4: The right image (b) is higher in contrast than the left image (a)

1.2.4 Image histogram

The histogram describes the relative color amount in a channel of an image.Since a pixel can have a value from 0 to 255,one can use the 256 get/put memory cells which contain the total amount of pixels having that certain pixel value.The frequency of each pixel value in an image is computed with the following formula.The visualization of a histogram is done with a bar graph.

1.2.5 Digital processing of camera images

Digital cameras generally include dedicated digital image processing chips to convert the raw data from the image sensor into a color-corrected image in a standard image file format. Images from digital cameras often receive further processing to improve their quality, a distinct advantage digital cameras have over film cameras. The digital image processing is typically done by special software programs that can manipulate the images in many ways.

Many digital cameras also enable viewing of histograms of images, as an aid for the photographer to better understand the rendered brightness range of each shot. [http: image basics]

1.3 Objective of work

The objective of research project is the development of a noise reduction technique which can be used to decrease the visible noise in magnetic resonance images(MRI) using various filters with the help of MATLAB software.

Chapter 2
Image Noise

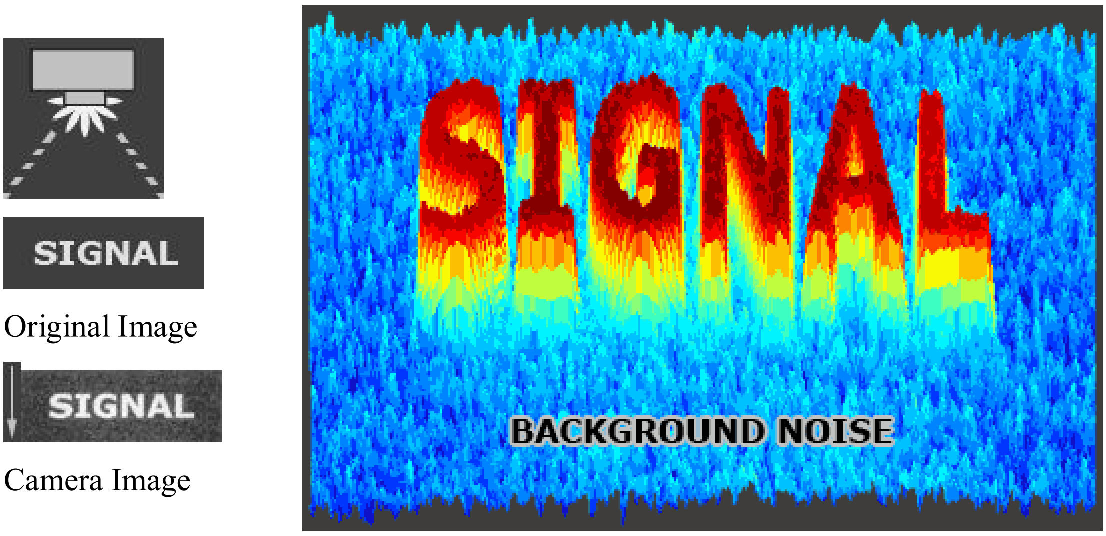
2.1 Noise in Images

Image noise is a random, usually unwanted, fluctuation of pixel values in an image. Image noise can originate in film grain, or in electronic noise in the input device (scanner or digital camera) sensor and circuitry, or in the unavoidable shot noise of an ideal photon detector. Image noise is most apparent in image regions with low signal level, such as shadow regions or underexposed images.

"Image noise" is the digital equivalent of film grain for analogue cameras. Alternatively, one can think of it as analogous to the subtle background hiss you may hear from your audio system at full volume. For digital images, this noise appears as random speckles on an otherwise smooth surface and can significantly degrade image quality. Although noise often detracts from an image, it is sometimes desirable since it can add an old-fashioned, grainy look to an image which is reminiscent of of early film. Some noise can also increase the apparent sharpness of an image. Noise increases with the sensitivity setting in the camera, length of the exposure, temperature, and even varies amongst different camera models. [http: image noise]

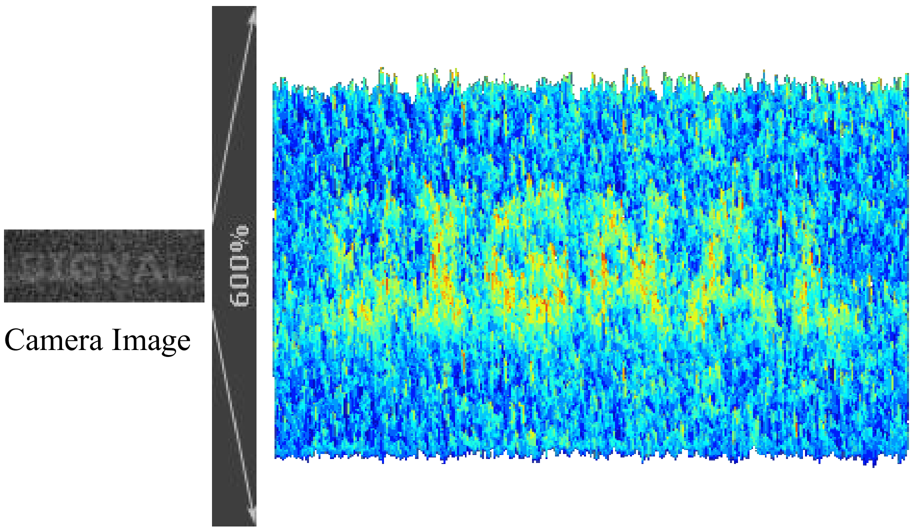
2.2 Concept

Some degree of noise is always present in any electronic device that transmits or receives a "signal." For televisions this signal is the broadcast data transmitted over cable or received at the antenna; for digital cameras, the signal is the light which hits the camera sensor. Even though noise is unavoidable, it can become so small relative to the signal that it appears to be nonexistent. The signal to noise ratio (SNR) is a useful and universal way of comparing the relative amounts of signal and noise for any electronic system; high ratios will have very little visible noise whereas the opposite is true for low ratios. The sequence of images below show a camera producing a very noisy picture of the word "signal" against a smooth background. The resulting image is shown along with an enlarged 3-D representation depicting the signal above the background noise. [http: noise]



(a)

Fig 2.1 has a sufficiently high SNR to clearly separate the image information from background noise. A low SNR would produce an image where the "signal" and noise are more comparable and thus harder to discern from one another.



(b)

FIG 2.1(a,b) : 3-D representation of the camera's image

2.3 The Cause: Sensor Noise

Each pixel in a camera sensor contains one or more light sensitive photodiodes which convert the incoming light (photons) into an electrical signal which is processed into the color value of the pixel in the final image. If the same pixel would be exposed several times by the same amount of light, the resulting color values would not be identical but have small statistical variations, called "noise". Even without incoming light, the electrical activity of the sensor itself will generate some signal, the equivalent of the background hiss of audio equipment which is switched on without playing any music. This additional signal is "noisy" because it varies per pixel (and over time) and increases with the temperature, and will add to the overall image noise. It is called the "noise floor". The output of a pixel has to be larger than the noise floor in order to be significant (i.e. to be distinguishable from noise).

2.4 The Effect: Image Noise

Noise in digital images is most visible in uniform surfaces (such as blue skies and shadows) as monochromatic grain, similar to film grain (luminance noise) and/or as colored waves (color noise). As mentioned earlier, noise increases with temperature. It also increases with sensitivity, especially the color noise in digital compact cameras (example D below). Noise also increases as pixel size decreases, which is why digital compact cameras generate much noisier images than digital SLRs. Professional grade cameras with higher quality components and more powerful processors that allow for more advanced noise removal algorithms display virtually no noise, especially at lower sensitivities.

Noise is typically more visible in the red and blue channels than in the green channel. This is why the unmagnified red channel crops in the examples below are better at illustrating the differences in noise levels.

2.5 Sources of Noise in Digital Images

Digital images are prone to a variety of types of noise. Noise is the result of errors in the image acquisition process that result in pixel values that do not reflect the true intensities of the real scene. There are several ways that noise can be introduced into an image, depending on how the image is created. For example:

- If the image is scanned from a photograph made on film, the film grain is a source of noise. Noise can also be the result of damage to the film, or be introduced by the scanner itself.
- If the image is acquired directly in a digital format, the mechanism for gathering the data (such as a CCD detector) can introduce noise.
- Electronic transmission of image data can introduce noise.

2.6 Noise characteristics

Noise not only changes depending on exposure setting and camera model, but it can also vary within an individual image. For digital cameras, darker regions will contain more noise than the brighter regions; with film the inverse is true.

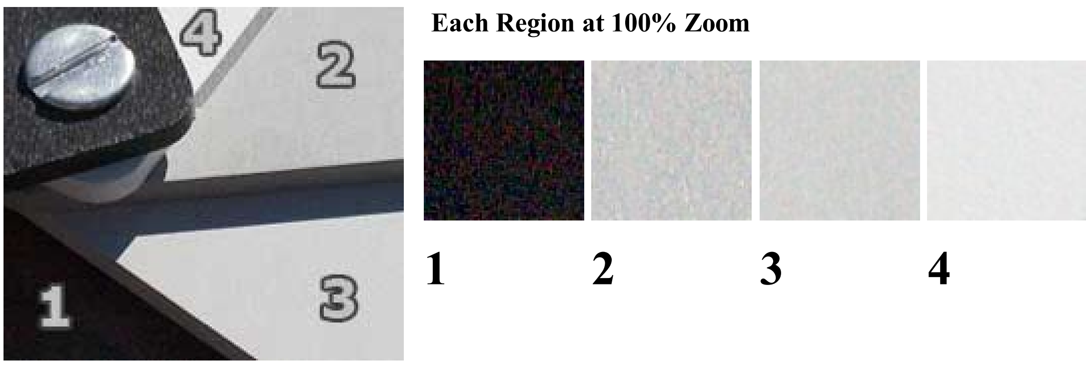


FIG 2.2: Noise characteristics

Note how noise becomes less pronounced as the tones become brighter. Brighter regions have a stronger signal due to more light, resulting in a higher overall SNR. This means that images which are underexposed will have more visible noise--even if you brighten them up to a more natural level afterwards. On the other hand, overexposed images will have less noise and can actually be advantageous, assuming that you can darken them later and that no region has become solid white where there should be texture .

Noise is also composed of two elements: fluctuations in color and luminance. Color or "chroma" noise is usually more unnatural in appearance and can render images unusable if not kept under control. The example below shows noise on what was originally a neutral grey patch, along with the separate effects of chroma and luminance noise.

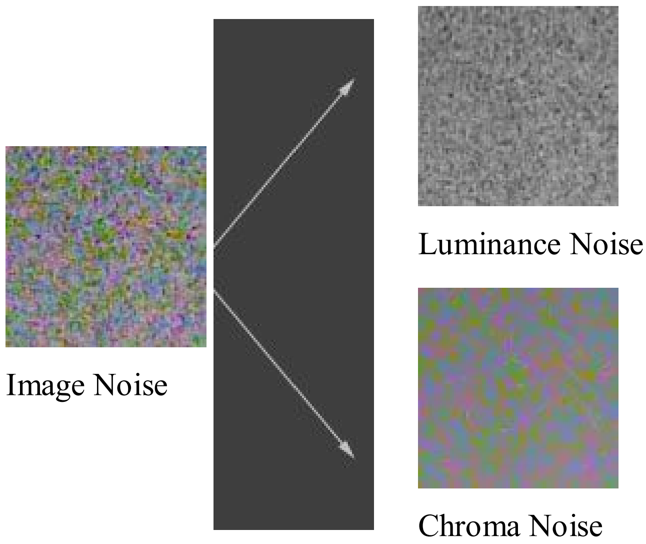
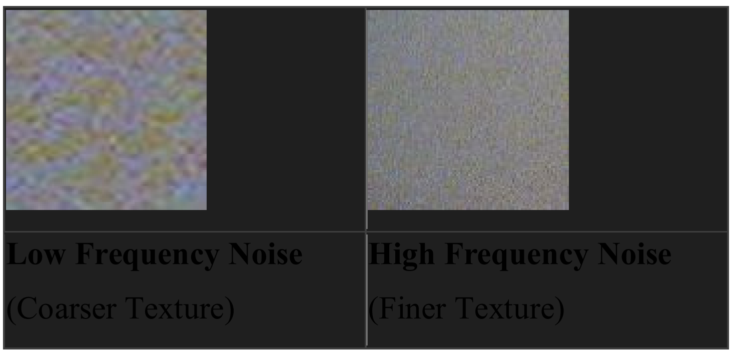


FIG 2.3: Elements of noise

The relative amount of chroma and luminance noise can vary significantly from one camera model to another. Noise reduction software can be used to selectively reduce both chroma and luminance noise, however complete elimination of luminance noise can result in unnatural or "plasticy" looking images.

Noise fluctuations can also vary in both their magnitude and spatial frequency, although spatial frequency is often a neglected characteristic. The term "fine-grained" was used frequently with film to describe noise whose fluctuations occur over short distances, which is the same as having a high spatial frequency. The example below shows how the spatial frequency can change the appearance of noise.



Standard Deviation: 11.7	Standard Deviation: 12.5

FIG 2.4: Variation in spatial frequency

If the two patches above were compared based solely on the magnitude of their fluctuations (as is done in most camera reviews), then the patch on the right would seem to have higher noise. Upon visual inspection, the patch on the right actually appears to be much less noisy than the patch on the left. This is due entirely to the spatial frequency of noise in each patch.

Even though noise's spatial frequency is under emphasized, its magnitude still has a very prominent effect. The next example shows two patches which have different standard deviations, but the same spatial frequency.

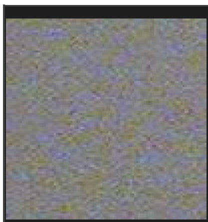
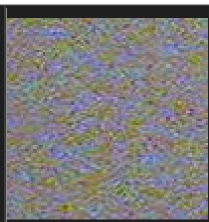
	
Low Magnitude Noise (Smoother Texture) Standard Deviation: 11.7	**High Magnitude Noise** (Rougher Texture) Standard Deviation: 20.8

FIG 2.5: Variation in magnitude

Note how the patch on the left appears much smoother than the patch on the right. High magnitude noise can overpower fine textures such as fabric or foliage, and can be more difficult to remove without over softening the image. The magnitude of noise is usually described based on a statistical measure called the "standard deviation," which quantifies the typical variation a pixel will have from its "true" value. This concept can also be understood by looking at the histogram for each patch:

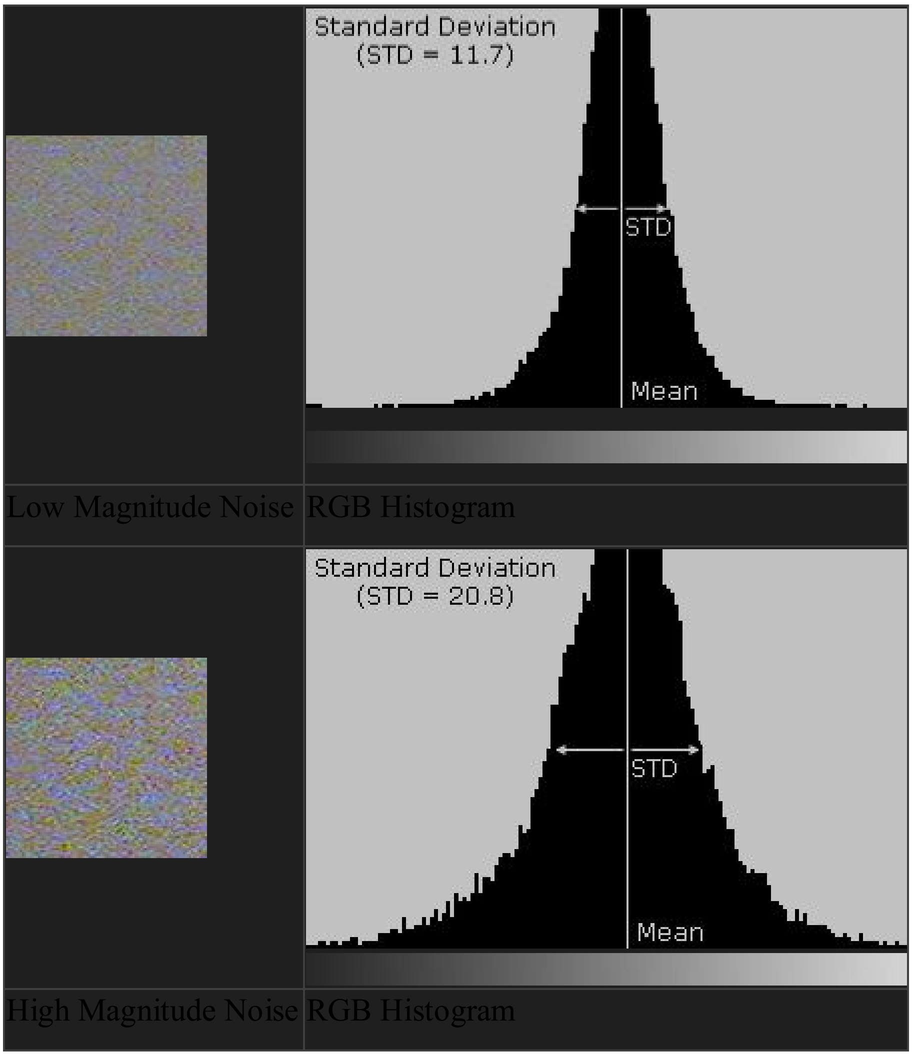


FIG 2.6: Low and high magnitude RGB histogram

If each of the above patches had zero noise, all pixels would be in a single line located at the mean. As noise levels increase, the width of this histogram shaped like a bell curve also increases. We present this for the RGB histogram, although the same comparison can also be made for the luminosity (most common measure of overall noise) and individual color histograms. [http: noise characteristics]

2.7 Types of noise

The noise affecting images can be classified according to various different types :

a) Shot noise
b) Salt and pepper noise
c) Coherent noise

d) Gaussian noise
e) Poison noise
f) Speckle noise
g) Additive Gaussian noise

Other types that depend on the particular image sensor design may include various fixed-pattern and row/column noises, such as pixel fixed-pattern noise, column fixed-pattern noise, random row noise, etc.

2.7.1 SHOT NOISE

Shot noise is a type of electronic noise that occurs when the finite number of particles that carry energy, such as electrons in an electronic circuit or photons in an optical device, is small enough to give rise to detectable statistical fluctuations in a measurement. It is important in electronics, telecommunications, and fundamental physics.

The strength of this noise increases with the average magnitude of the current or intensity of the light. However, since the magnitude of the average signal increases more rapidly than that of the shot noise, shot noise is often only a problem with small currents or light intensities.

The intensity of a source will yield the *average* number of photons collected, but knowing the average number of photons which will be collected will not give the actual number collected. The actual number collected will be more than, equal to, or less than the average, and their distribution about that average will be a Poisson distribution.

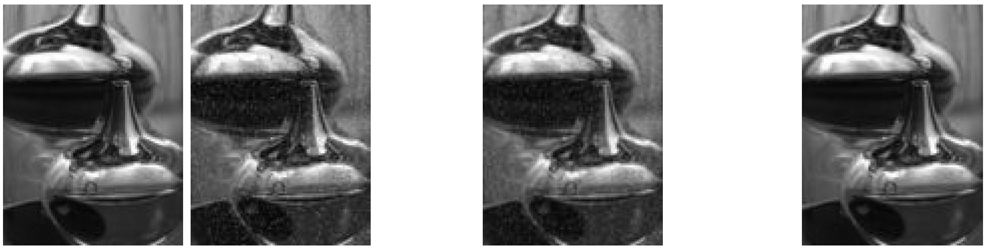
Since the Poisson distribution approaches a normal distribution for large numbers, the photon noise in a signal will approach a normal distribution for large numbers of photons collected. The standard deviation of the photon noise, is equal to the square root of the average number of photons. The signal-to-noise ratio is then

$$SNR = \frac{N}{\sqrt{N}} = \sqrt{N}$$

where N is the average number of photons collected. When N is very large, the signal-to-noise ratio is very large as well. It can be seen that photon noise becomes more important when the number of photons collected is small.

2.7.2 SALT AND PEPPER NOISE

Salt and pepper noise is a form of noise typically seen on images. It represents itself as randomly occurring white and black pixels. Usual and effective noise reduction method for this type of noise involves the usage of median filter. Below is an example of original image, original image deteriorated by salt and pepper noise, deteriorated image repaired using averaging filter and deteriorated image repaired using median filter.



Original image.	Image with added salt and pepper noise.	Reconstructed image using average filter.	Reconstructed image using median filter.

FIG 2.7: Effect of salt and pepper noise

2.7.3 COHERENT NOISE

Coherent noise is generated by a *coherent-noise function*, which has three important properties:

1. Passing in the same input value will always return the same output value.
2. A small change in the input value will produce a small change in the output value.
3. A large change in the input value will produce a random change in the output value.

An n-dimensional coherent-noise function requires an n-dimensional input value. Its output value is always a scalar. An image with coherent noise is shown in fig 2.8

Fig 2.8: Image with coherent noise

2.7.4 GAUSSIAN NOISE

In communications, a random interference generated by the movement of electricity in the line. It is similar to white noise, but confined to a narrower range of frequencies. You can actually see and hear Gaussian noise when you tune your TV to a channel that is not operating. Contrast with white noise and pink noise.

A random distribution of artifacts in analog video images that makes everything look soft and slightly blurry. On close inspection, one can see tiny specks in random patterns. Found on films shot with older cameras as well as films and videotapes that have been archived for a long time, dynamic noise reduction (DNR) circuits can eliminate. much of the Gaussian noise when the analog material is converted to digital.

Gaussian noise is noise that has a probability density function (abbreviated pdf) of the normal distribution (also known as Gaussian distribution). In other words, the values that the noise can take on are Gaussian distributed. It is most commonly used as additive white noise to yield additive white Gaussian noise (AWGN). Gaussian noise is properly defined as noise with a Gaussian amplitude distribution. This says nothing of the correlation of the noise in time or of the spectral density of the noise. Labeling Gaussian noise as 'white' describes the correlation of the noise.

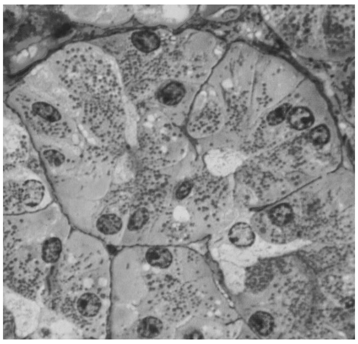


Fig2.9: Grayscale image

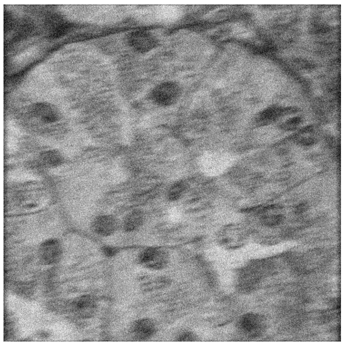


Fig 2.10: Degraded image with Gaussian noise

2.7.5 Poisson noise

"Poisson noise" generates a noise sequence of integer numbers having a Poisson probabilitydistribution

$$p(x) = \frac{\mu^x}{x!} \cdot e^{-\mu}$$

with μbeing the expectation value (E).

The input parameters are

- Length N (in samples) and
- Expectation E.

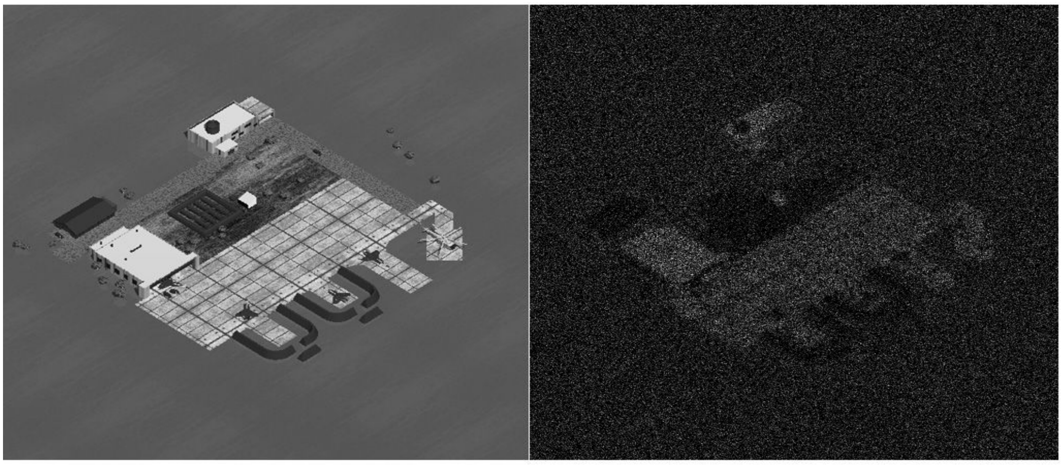


Fig 2.11: Original image(left) and image degraded by poisson noise(right)

2.7.6 Speckle noise

Speckle is a random, deterministic, interference pattern in an image formed with coherent radiation of a medium containing many sub-resolution scatterers. The texture of the observed speckle pattern does not correspond to underlying structure. The local brightness of the speckle pattern, however, does reflect the local echogenicity of the underlying scatterers. Speckle noise is also known as modal noise which is the noise generated in an optical fiber system by the combination of mode-dependent optical losses and fluctuation in the distribution of optical energy among the guided modes or in the relative phases of the guided modes.

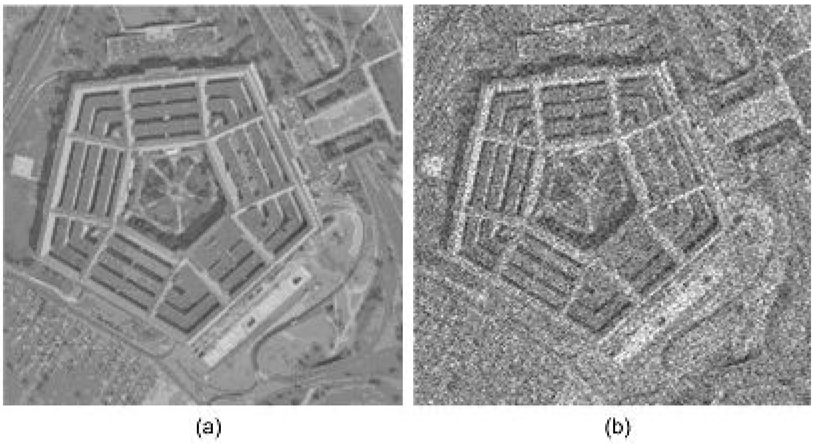


Fig 2.12(a,b): Original image(a) and image degraded by speckle noise(b)

2.8 Common sources of blurring and noise

Blurring is present in any imaging system which uses electromagnetic radiation (for example, visible light and X-rays). Diffraction limits the resolution of an imaging device to features on the order of the illuminating wavelength. Scattering of light between the target object and imaging system (for example, by the atmosphere) introduces additional blurring. Lenses and mirrors cause blurring because they have limited spatial extent and optical imperfections. Discretization results in yet more blurring because devices such as CCDs average illumination over regions rather than sampling it at discrete points.

Noise is similarly omnipresent: any imaging device must use a finite exposure (or integration) time, which introduces stochastic noise from the random arrival of photons. Optical imperfections and instrumentation noise (for example, thermal noise in CCD devices) result in more noise. Sampling causes noise due to aliasing of high-frequency signal components, and digitization produces quantization errors. Further noise can be introduced by communication errors and compression.

Blurring and noise processes can be accurately approximated by mathematical models.

It is generally desirable for image brightness (or film density) to be uniform except where it changes to form an image. There are factors, however, that tend to produce variation in the brightness of a displayed image even when no image detail is present. This variation is usually random and has no particular pattern. In many cases, it reduces image quality and is especially significant when the objects being imaged are small and have relatively low contrast. This random variation in image brightness is designatednoise.

All medical images contain some visual noise. The presence of noise gives an image a mottled, grainy, textured, or snowy appearance. The figure below compares two images with different levels of noise. Image noise comes from a variety of sources, as we will soon discover. No imaging method is free of noise, but noise is much more prevalent in certain types of imaging procedures than in others.

Nuclear images are generally the most noisy. Noise is also significant in MRI, Computer Tomography and ultrasound imaging. In comparison to these, radiography produces images with the least noise. Fluoroscopic images are slightly more noisy than radiographic images, for reasons explained later. Conventional photography produces relatively noise-free images except where the grain of the film becomes visible.

CHAPTER 3
Magnetic Resonance Imaging

3.1 Background

Magnetic Resonance Imaging (MRI) is a powerful imaging technique that is an extension of the phenomena of Nuclear Magnetic Resonance (NMR). NMR relies on the fact that atomic nuclei with a non-zero spin have a magnetic moment. In medical imaging it is usually the nuclei of hydrogen atoms (i.e. protons) are usually studied since they are present in the body in high concentrations (e.g. as water). In an object that contains a large number of nuclei the random motion of atoms gives the object no net magnetisation. However, in a homogeneous magnetic field, B_0, the nuclei undergo Zeeman splitting producing energy levels with an energy difference of $hn_0 = g B_0$, where g is the gyromagnetic ratio for hydrogen and n_0 is the Lamour frequency. For hydrogen the Lamour frequency at 1 Tesla is 42.6 MHz. Thus at the low field of interest to this programme (approx. 0.01 T) the Lamour frequency is around 400 kHz. Simplistically it can be imagined that the magnetic moments have lined up with the field to give the body a net magnetisation, M_0, parallel and proportional B_0. The application of an RF field at the Lamour frequency perpendicular to B_0 will cause the nuclei to become excited which in turn causes the net magnetisation vector to precess about B_0. When the RF signal is removed the net magnetisation decays to its equilibrium alignment, emitting an RF signal at the Lamour frequency. This signal can be detected by a receive coil and used for NMR spectroscopy or MRI. The size of the signal increases with M_0 and thus with B_0, this is the reason that conventional MRI systems use a high magnetic field. This project aims to extract the maximum information from the small signal at low field rather than using expensive high field magnets to generate more signal.

To obtain an image from the NMR signal requires a method for extracting spatial information from the signal. This is achieved by a combination of techniques. First a field gradient is superimposed over B_0 so that a 2D slice of the sample can be selected, i.e. only a slice of the sample sees a magnetic field to give a Lamour frequency that matches the coil and electronics. Then complex sequences of RF pulses and Fourier transforms are used to extract spatial information in the 2D slice.

To make imaging possible the signal to noise ratio (SNR) must be increased to an acceptable level. In conventional scanners this has been achieved by increasing the magnetic field, which increases the signal. The magnetic field must also be very uniform and stable over the imaging area. This has led to machines which use expensive high field (1 Tesla or greater) superconducting magnets. Not only are these machines expensive in terms of capital cost, they also have high running costs and space requirements. [http: mri]

3.2 MRI Physics

When a person is in the scanner, the hydrogen nuclei(i.e., protons) found in abundance in the human body in water molecules, align with the strong magnetic field. A radio wave at just the right frequency for the protons to absorb energy pushes some of the protons out of alignment. The protons then snap back to alignment, producing a detectable rotating magnetic field as they do so. Since protons in different tissues of the body (e.g., fat v. muscle) realign at different speeds, the different structures of the body can be revealed.

Gradient fields in the three dimensions allow the scanner to work only with protons from a "slice" at a time, allowing the creation of a whole volume that can be looked at in three dimensions.

Contrast agents may be injected intravenously to show enhancement of blood vessels, tumors or inflammation. Unlike CT scanning MRI uses no ionizing radiation and is generally a very safe procedure. Patients with some metal implants and cardiac pacemakers are prevented from having an MRI due to effects of the powerful magnetic field and powerful radio waves.

MRI is used to image every part of the body, but is particularly useful in neurological conditions, disorders of the muscles and joints, for evaluating tumors and showing abnormalities in the heart and blood vessels.

FIG 3.1: Modern 3 tesla clinical MRI scanner

3.3 Imaging

A number of schemes have been devised for combining field gradients and radiofrequency excitation to create an image. One involves 2D or 3D reconstruction from projections, much as in Computed Tomography. Others involve building the image point-by-point or line-by-line. One even uses gradients in the rf field rather than the static field. Although each of these schemes is occasionally used in specialist applications, the majority of MR Images today are created either by the Two-Dimensional Fourier Transform (2DFT) technique with slice selection, or by the Three-Dimensional Fourier Transform (3DFT) technique. Another name for 2DFT is spin-warp. Slice selection is achieved by applying a magnetic gradient in addition to the external magnetic field during the radio frequency pulse. Only one plane within the object will have protons that are on–resonance and contribute to the signal.

A real image can be considered as being composed of a number of spatial frequencies at different orientations. A two–dimensional Fourier transformation of a real image will express these waves as a matrix of spatial frequencies known as k–space. Low spatial frequencies are represented at the center of k–space and high spatial frequencies at the periphery. Frequency and phase encoding are used to measure the amplitudes of a range of spatial frequencies within the object being imaged.

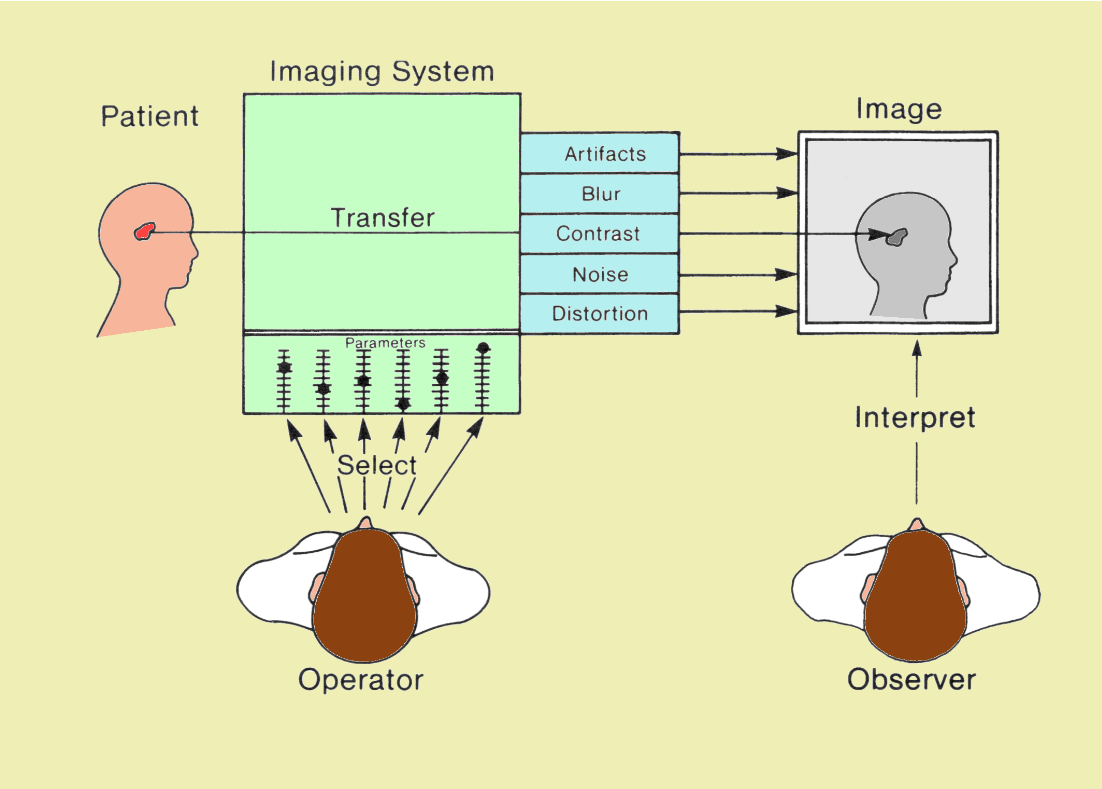


FIG 3.2: Components Associated with the Medical Imaging Process

The frequency encoding gradient is applied during readout of the signal and is orthogonal to the slice selection gradient. During application of the gradient the frequency differences in the readout direction progressively change. At the midpoint of the readout these differences are small and the low spatial frequencies in the image are sampled filling the center of k-space. Higher spatial frequencies will be sampled towards the beginning and end of the readout filling the periphery of k-space. Phase encoding is applied in the remaining orthogonal plane and uses the same principle of sampling the object for different spatial frequencies. However, it is applied for a brief period before the readout and the strength of the gradient is changed incrementally between each radio frequency pulse. For each phase encoding step a line of k–space is filled. Either a spin echo or a gradient echo can be used to refocus the magnetisation.

The 3DFT technique is rather similar except that there is no slice selection and phase-encoding is performed two separate directions. Another scheme which is sometimes used, especially in brain scanning or where images are needed very rapidly, is called echo-planar imaging (EPI): in this case each rf excitation is followed by a whole train of gradient echoes with different spatial encoding.

3.4 Noise Issues

Perhaps the most significant technical challenge in functional MRI is the small size of the activation related response. This has commonly been reported to be in the 1-4% range for imaging at the most common magnetic field strength - 1.5 Tesla. Noise in functional MRI comes from a variety of sources. In most MR imaging, the standard sources of noise are thermal noise from the subject (the human body is full of ions and electrons bouncing around generating electromagnetic noise), reception coil, preamplifiers and other electronics, and quantization noise from the analog to digital conversion. In functional MRI, it as also been observed that there are variations in the received signal that correlate strongly with the respiratory and cardiac cycles.These sources have been verified through independent acquisition of respiration and cardiac signals from a blood pulse oximeter and pneumatic systems for monitoring chest wall movement.

Another significant source of signal variations in functional MRI is head movement. Consider an object edge in which image intensity change of DI. A fractional pixel movement of size DX, can cause the image intensity to vary by about DIxDX. At an object boundary, then, movements that are a small fraction of pixel can cause signal changes that are greater than the activation response of 1-4%. For common pixel dimensions of 1-3 mm, even a movement of 100 mm is problematic. There are also a variety of very slow signal drifts in image intensity that have been observed. These drifts, which appear in human subjects but not in inanimate phantoms, have a time course characterized in several to tens of minutes and are spatially variant. The suspected sources of these signal drifts include physiological state of the subject, equipment instability, and settling of the head into padding. Finally, uncontrolled or spontaneous neuronal events represents yet another source of noise. In the context of a functional imaging study this source of noise includes differences in the manner in which a task is performed, neuronal events associated with behavior (conscious or otherwise) unrelated to the task, and spontaneous firing of networks (consolidation processes, etc.).

In the image below we find our familiar array of body objects arranged according to physical contrast and size. We now add a third factor, noise, which will affect the boundary between visible and invisible objects. The general effect of increasing image noise is to lower the curtain and reduce object visibility. In most medical imaging situations the effect of noise is most significant on the low-contrast objects that are already close to the visibility threshold.

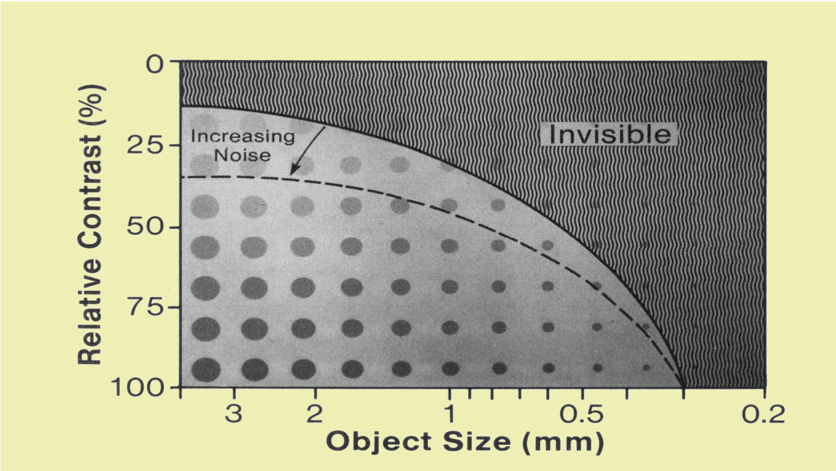


FIG 3.3: Effect of Noise on Object Visibility

There are a number of approaches to addressing noising fMRI data. First, all of the standard methods for improve the signal-to-noise ratio (SNR) with respect to thermal noise also apply to fMRI. This include using special reception coils, for example those designed to receive from specific parts of the brain, and using high field scanners, which increases the equilibrium magnetization as well as increasing the magnetic field non-uniformity's from the paramagnetic effects of deoxy-Hb (increases the size of the fMRI signal changes). In addition to these hardware solutions, one can commonly trade spatial and temporal resolution for improved SNR. In one formulation, the SNR equation for an MR image is:

$$SNR = M\, V\ \sqrt{T_{A/D}}$$

The parameter M in this relationship is the magnetization, which is a function of tissue parameters (T1, T2 or T2*, spin density), imaging parameters (TR, TE, flip angle), and field strength, B0. The parameter V is the voxel volume and $T_{A/D}$ represents the total time spent sampling k-space for a given image. Clearly, there are many factors that can be manipulated to improve the image SNR, but for fMRI, the most significant ones include lowering the spatial resolution (increasing V), using a high field strength magnet (B0), lengthening imaging times.

Depending on the spatial resolution and field strength, however, other sources of noise may be more important. In these cases, the traditional methods for improving the signal-to-noise ratio, such as using larger voxels, may offer only a small improvement to the fMRI data. These other sources of noise in functional MRI experiments are not as easily understood and new methods must be developed to correct for their effects. For example, one approach to minimizing the undesired effects of cardiac and respiratory variability and head movement is to use rapid acquisition techniques such as echo-planar imaging (EPI) and spiral imaging . Rapid imaging allows physiological motion to be frozen so that it does contribute to intra-image data inconsistency. It also allows for a large number of images to be averaged in an attempt to reduce the undesired physiologic variations. Other approach to address pulmonary and cardiac noise are to gate or reorder data acquisition according the phases of the physiological cycle. It is also possible to acquire information about the physiological effects during at each acquisition and use this information to correct the data as part of the image reconstruction process .

Specific steps can be taken to reduce the effects of slow drifts in the MRI signal as well as head movement. One way to address these considerations is to repeat each behavioral state multiple times and ordering these states in an alternating, counter-balanced, or randomized ordering. These condition ordering schemes can also be used to address trends related subject performance and learning throughout the experiment . Post-processing strategies include removal of linear (high pass filtering) order drifts terms prior to statistical analyses and normalization of global image intensities.

3.5 Quality Control Issues in MRI

3.5.1 Low Noise

Grey values in MRI reflect two components: (a) signal intensity and (b) unavoidable noise. Noise is, in principle, unavoidable. It is caused by: (a) electromagnetic noise in the body due to movement of charged particles and (b) small anomalies in the measurement electronics, which depends on (a) the size of the RF coil and (b) the bandwidth of the pulse sequence. (Large coils have a large measurement field, but low SNR and vice versa. The closer the coil to the object, the stronger the signal – the smaller the volume, the higher the SNR. Wider bandwidths decrease SNR.)

The signal-to-noise ratio (SNR) is a criterion for image quality. The SNR increases in proportion to voxel volume (1/resolution), the square root of the number of acquisitions (NEX), and the square root of the number of scans (phase encodings). SNR decreases with the field of view squared (FOV^2). Measuring SNR: record the mean value of a small region of interest (ROI) placed in the most homogeneous area of tissue with high signal intensity (eg, white matter in thalamus). Calculate the standard deviation for the largest possible ROI placed outside the object in the image background (avoid ghosting/aliasing or eye movement artifact regions). The SNR is then:

Mean Signal / standard Deviation of Background Noise

For example, suppose mean signal is 720 and st.dev. of background is 20, the SNR is 720/20, which is 36.

3.5.2 Resolution

Resolution is a function of slice thickness, Field of View (FOV), and matrix size. The in-plane resolution is a function of FOV / matrix size.

As slice thickness increases, signal intensity and SNR increase, but the spatial resolution decreases perpendicular to the slice. Thinner slices are less susceptible to partial volume effects. The number of slices for a 2D pulse sequences is a factor of the selected TR / minimum TR. (Slice distance is a factor of slice gap / slice thickness. If slice distances are too small, there is cross talk between slices that can affect T1 contrast. This can be reduced by selection of interleaved slices, but interleaved slice acquisition can produce large mean intensity differences between adjacent slices.)

The FOV is the square image area that contains the object of interest to be measured. The smaller the FOV, the higher the resolution and the smaller the voxel size. SNR decreases with the FOV^2. For example, decreasing the FOV from 350 to 240 mm drops the SNR by more than 50%. (Smaller FOV required higher gradient strength.)

A FOV of about 256 mm is common for brain imaging.

The image matrix size is the number of rows multiplied by the number of columns. A 128x256 matrix consists of 128 rows and 256 columns. The rows or lines are each scanned separately (phase encoding), while the columns are scanned simultaneously (frequency encoding). The columns usually determine the matrix size.

Matrix size effects scan time, resolution and SNR. The measurement time is a function of the number of scans (phase encoding steps) x TR x number of excitations (NEX). In-plane resolution is a function of FOV / matrix size. For instance, with a FOV of 256 mm and a matrix of 128x128, resolution is 2mm, but a matrix of 256x256 gives a 1mm resolution. The SNR is proportional to the square root of the number of scans (rows) and the voxel volume (relative SNR = change of voxel size * sqrt[change # scans]). For example, given a FOV of 256 mm, a reduction from 256x256 to 128x128 increases voxel size by 4 times and decreases the phase encoding steps by 2; SNR improves by a factor of $4 * \frac{1}{\sqrt{2}} = 2.82$, more than double. (Note, to retain the same SNR for a 512x512 matrix over a 256x256 matrix, 8 NEX are required and measurement time increases by 16 because the number of scans is doubled.)

An image matrix of 256x256 is common for high resolution brain imaging, but 128x128 or 64x64 is preferable for functional brain imaging to decrease measurement time.

Area resolution is a factor of the FOV / matrix size. The voxel size reflects the spatial resolution, which is a factor of area resolution and slice thickness ([FOV / matrix] * thickness). The smaller the voxel, the higher the spatial resolution, but the lower the SNR. A loss of SNR while attaining higher spatial resolution can be offset by an increase in the number of acquisitions (NEX) and a longer TR (but this will alter contrast).

Consider the figure below. The task of every imaging system is to translate a specific tissue characteristic into image shades of gray or color. If contrast is adequate, the object will be visible. The degree of contrast in the image depends on characteristics of both the object and the imaging system.

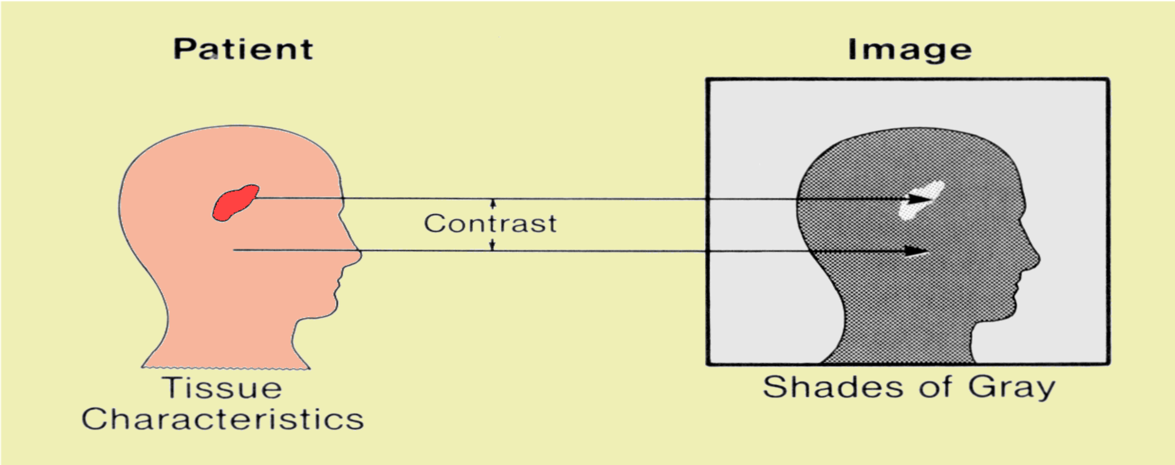


FIG 3.4: Medical Imaging is the Process of Converting Tissue Characteristics into a Visual Image

3.5.3 Image Contrast

Contrast means difference. In an image, contrast can be in the form of different shades of gray, light intensities, or colors. Contrast is the most fundamental characteristic of an image. An object within the body will be visible in an image only if it has sufficient physical contrast relative to surrounding tissue. However, image contrast much beyond that required for good object visibility generally serves no useful purpose and in many cases is undesirable. The physical contrast of an object must represent a difference in one or more tissue characteristics. For example, in radiography, objects can be imaged relative to their surrounding tissue if there is an adequate difference in either density or atomic number and if the object is sufficiently thick.

When a value is assigned to contrast, it refers to the difference between two specific points or areas in an image. In most cases we are interested in the contrast between a specific structure or object in the image and the area around it or its background.

3.5.4 Contrast Sensitivity

The degree of physical object contrast required for an object to be visible in an image depends on the imaging method and the characteristics of the imaging system. The primary characteristic of an imaging system that establishes the relationship between image contrast and object contrast is its contrast sensitivity. Consider the situation shown below. The circular objects are the same size but are filled with different concentrations of iodine contrast medium. That is, they have different levels of object contrast. When the imaging system has a relatively low contrast sensitivity, only objects with a high concentration of iodine (ie, high object contrast) will be visible in the image. If the imaging system has a high contrast sensitivity, the lower-contrast objects will also be visible.

The contrast transfer characteristic of an imaging system can be considered from two perspectives. From the perspective of adequate image contrast for object visibility, an increase in system contrast sensitivity causes lower-contrast objects to become visible. However, if we consider an object with a fixed degree of physical contrast (i.e., a fixed concentration of contrast medium), then increasing contrast sensitivity will increase image contrast.ill also be visible. [http: quality]

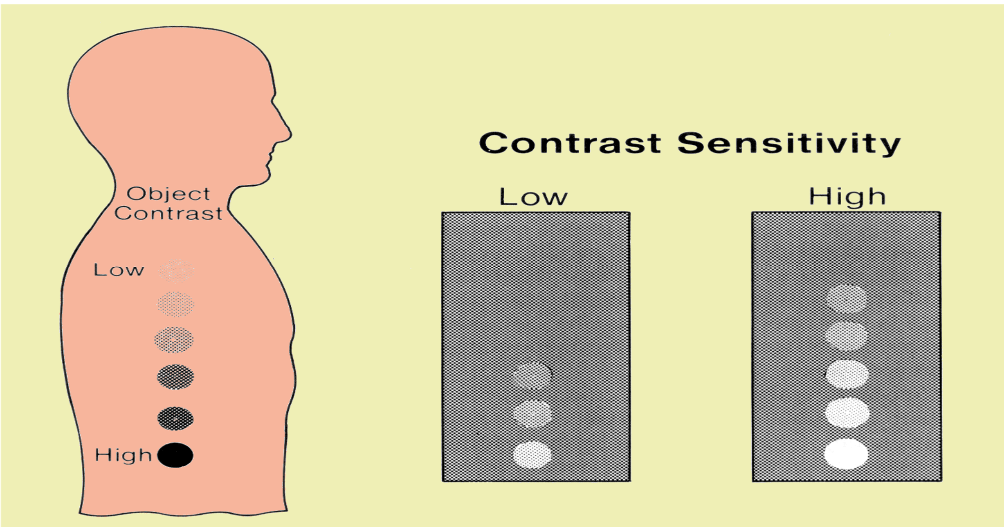


FIG 3.5: Increasing contrast sensitivity the image contrast and the visibility of objects in the body increases

3.6 Signal-to-noise ratio

Noise is like interferences which present as a irregular granular pattern. This random variation in signal intensity degrades image information. The main source of noise in the image is the patient's body (RF emission due to thermal motion). The whole measurement chain of the MR scanner (coils, electronics...) also contributes to the noise. This noise corrupts the signal coming from the transverse magnetization variations of the intentionally excited spins (on the selected slice plane). The signal to noise ratio (SNR) is equal to the ratio of the average signal intensity over the standard deviation of the noise.

The signal to noise ratio depends both on some factors that are beyond the operator's control (the MR scanner specifications and pulse sequence design) and on factors that the user can change:

- **Fixed factors :** static field intensity, pulse sequence design, tissue characteristics
- **Factors under the operator's control**
    - RF coil to be used
    - Sequence parameters : voxel size (limiting spatial resolution), number of averagings, receiver bandwidth

The signal to noise ratio is used in MRI to describe the relative contributions to a detected signal of the true signal and random superimposed signals ('background noise'). One common method to increase the SNR is to average several measurements of the signal, on the expectation that random contributions will tend to cancel out. The SNR can also be improved by sampling larger volumes (increasing the field of view and slice thickness with a corresponding loss of spatial resolution) or, within limits, by increasing the strength of the magnetic field used. Surface coils can also be used to improve local signal intensity. The SNR will depend, in part, on the electrical properties of the sample or patient being studied. The SNR increases in proportion to voxel volume (1/resolution), the square root of the number of acquisitions (NEX), and the square root of the number of scans (phase encodings). [http: SNR]

CHAPTER 4
NOISE FILTERING

4.1 Concept of Noise Filtering

Image filtering makes possible several useful tasks in image processing. A filter can be applied to reduce the amount of unwanted noise in a particular image. Another type of filter can be used to reverse the effects of blurring on a particular picture. Yet another filter can be applied to soften or darken the color and brightness levels of an image. Although each of these functions produces a different result, they all rely on convolution to carry out their specified tasks.

Convolution provides the basis for many fundamental functions for both image and signal processing. Now that the basics of convolution have been presented, it is time to put this knowledge to use. Most specifically to image processing, convolution plays a crucial role in image filtering. From the basic mean filter, to the more complex Gaussian filter, convolution allows key operations to function. This is thanks to the unique mathematical nature of the convolution operation.

Image filtering makes possible several useful tasks in image processing. A filter can be applied to reduce the amount of unwanted noise in a particular image. Another type of filter can be used to reverse the effects of blurring on a particular picture. Yet another filter can be applied to soften or darken the color and brightness levels of an image. Although each of these functions produces a different result, they all rely on convolution to carry out their specified tasks.

The basic (and most common) technique used to filter an image is known as linear filtering. A linear filter convolves the image with a constant matrix, called a mask or kernel. The term linear in this case is due to the type of convolution that the filter is performing. Since the image is being convolved with a constant kernel, this models space- and time-invariant linear systems. In this aspect (consistent also with signal processing), the kernel can be viewed as the impulse response of the filter. Linear filters can be applied to both single- and multi-dimensional images. The basic idea of each filter is the same, with the multi-dimensional filter performing the filter operation in each dimension specified.

4.2 Filter characteristics

A filter is any kind of processing that has one characteristic: it takes a signal as the input and produces a relevant output signal after processing it in some way. A filter can *always* be mathematically described – think of it as a function, for instance:

$$y = f(x)$$

The least elaborate form of a simple filter that only takes one argument (an input signal or sample) and produces an output signal or sample

A filter can take any number of arguments that further define its behaviour – in fact, when designing a filter we usually need to give it a few guidelines according to which it will be built. In this article we will only be dealing with filters that are designed using one parameter – the dimensions – the contents of the filter we will choose carefully ourselves (no mathematical methods are discussed).

Notice that we defined the dimensions of a filter as one parameter – this hints that most filters have uniform side length. For a 1D filter this will define the length while for 2D filters the dimension will define the length of the sides. In essence one could also create 3D filters, but there aren't that many everyday uses for them.

An example of a 1D filter:

1	2	3	4	3	2	1

Notice one very important, although subtle, characteristic in 1D filter – the filter has an odd number of samples. This is a must for filters – the sample distribution doesn't have to be symmetrical (although usually it is) across the centre sample, but it must be possible to centre the filter over any sample in an input signal.

An example of a 2D filter:

$$\begin{matrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 2 & 2 & 2 & 1 \\ 1 & 2 & 3 & 2 & 1 \\ 1 & 2 & 2 & 2 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{matrix}$$

A 2D filter, too, has to have an odd number of samples in both the vertical as well as the horizontal orientation. The filters in eq 4.2 and 4.3 are not "real" – they were created randomly.

4.3 Smoothing

In digital image processing, noise removal or, more generally, image smoothing is one of the most important design goals of image enhancement. Most techniques, unfortunately, have the side effect of also blurring the image where this is undesirable, e.g. at sharp edges.

[http://www.ph.tn.tudelft.nl/Courses/FIP/noframes/fip-Smoothin.html]

Convolutional low-pass filter masks are, e.g.:

Averaging:

$$\frac{1}{5}\begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

Gaussian:

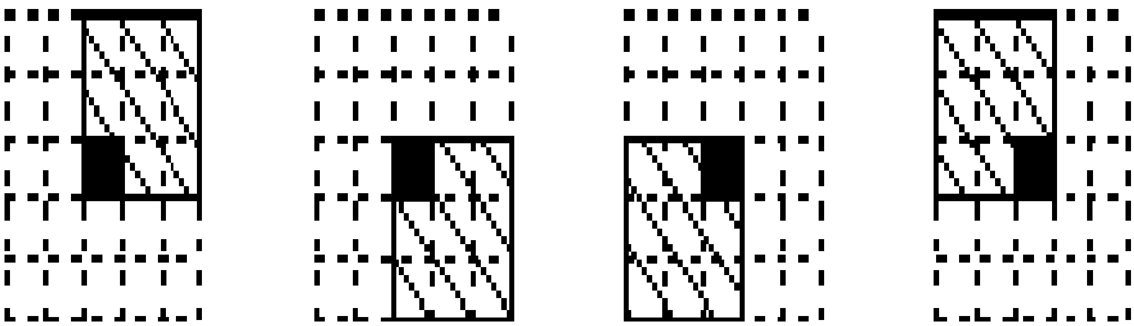
$$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

These methods reduce the noise, but usually they also blur the image at undesirable places. For larger masks (and if special convolver hardware is not available) it is preferable to do the convolution by passing to the frequency domain (convolution).[http: averaging]

Random noise can be removed preserving edges by using the median filter. An example for a different smoothing mask removing out-of-range pixels by convolution is

$$\frac{1}{8}\begin{matrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \end{matrix}$$

which computes the average of the eight neighbours; this must be used conditionally: to suppress impulse noise, the centre pixel is replaced by this average if it differs by more than a given threshold. Another method to smooth images preserving sharp edges is given in ; the method compares four different areas around the centre pixel as in the figure:



and replaces the centre pixel by the average of the most homogeneous area, the one with the smallest variance, where the variance is usually defined as:

$$\sigma^2(m,n) = \sum\sum[f(i,j) - \{f(m,n)\}]^2$$

with the sums taken over i, j $\in$N(m,n)and (f) denoting the average. [http: smoothing]

4.4 Smoothing Operators

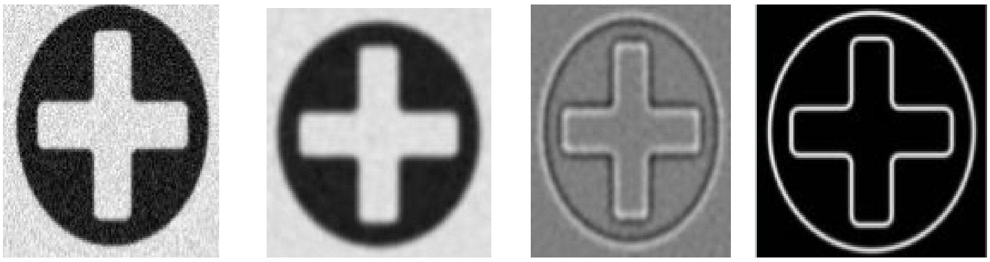
These operators are applied in order to reduce noise and/or to prepare images for further processing such as segmentation. We distinguish between linear and non-linear filters where the former are amenable to analysis in the Fourier domain and the latter are not. We also distinguish between implementations based on a rectangular support for the filter and implementations based on a circular support for the filter. Smoothers, or smoothing filters, are algorithms for time-series processing that reduce abrupt changes in the time-series and make it look smoother. Smoothers constitute a broad subclass of filters. Like all filters, smoothers may be subdivided into linear and nonlinear. Linear filters reduce the power of higher frequencies in the spectrum and preserve the power of lower frequencies. So they are classified as:

i) Linear filters

ii) Non-linear filters

4.4.1 Linear filters

Linear filters are the best understood of the neighborhood operations, due to the extensively developed mathematical framework of signal theory dating back 200 years to Fourier. Linear filters amplify or attenuate selected spatial frequencies, can achieve such effects as smoothing and sharpening., and usually form the basis of re-sampling and boundary detection algorithms. Linear filters can be defined by a convolution operation, where output pixels are obtained by multiplying each neighborhood pixel by a corresponding element of a likeshaped set of values called a kernel, and then summing those products. Figure a, for example, shows a rather noisy image of a cross within a circle. Convolution with the smoothing (low pass) kernel of figure b produces figure c. In this example the neighborhood is 25 pixels arranged in a 5x5 square. Note how the high frequency noise has been attenuated, but at a cost of some loss of edge sharpness. Note also that the kernel elements sum to 1.0 for unity gain. The smoothing kernel of figure b is a 2D Gaussian approximation. The 2D Gaussian is among the most important functions used for linear filtering. Its frequency response is also a gaussian, which results in a well-defined passband and no ringing. Kernels that approximate the difference of two Gaussians of different size make excellent band-pass and high-pass filters. Figure d illustrates the effect of a band-pass filter based on a difference of Gaussian approximation using a 10x10 kernel. Note that both the high frequency noise and the low frequency uniform regions have been attenuated, leaving only the mid-frequency components of the edges.



(a) (b) (c) (d)

Fig 4.1(a,b,c,d): An image can be enhanced to reduce noise or emphasize boundaries

Linear filters can be implemented by direct convolution or in the requency domain using FFTs. While frequency domain filtering is theoretically more efficient, in practice direct convolution is almost always preferred. Convolution, with its use of small integers and sequential memory addressing is a better match for digital hardware than FFTs ,is simpler to implement , and has little trouble with boundary conditions. Several linear filters are :

a) Uniform filter

The output image is based on a local averaging of the input filter where all of the values within the filter support have the same weight. For the discrete spatial domain [m,n] the filter values are the samples of the continuous domain case. Examples for the rectangular case (J=K=5) and the circular case (R=2.5) are shown in eqs .

$$h_{rect}[j,k] = \frac{1}{25}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \quad h_{circ}[j,k] = \frac{1}{21}\begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \end{bmatrix}$$

(a) Rectangular filter (J=K=5) (b) Circular filter (R=2.5)

Note that in both cases the filter is normalized so that $\sum h[j,k] = 1$. This is done so that if the input a[m,n] is a constant then the output image c[m,n] is the same constant. The justification can be found in the Fourier transform property described in eq. .. The square implementation of the filter is separable and incremental; the circular implementation is incremental .

b) Triangular filter

The output image is based on a local averaging of the input filter where the values within the filter support have differing weights. In general, the filter can be seen as the convolution of two (identical) uniform filters either rectangular or circular and this has direct consequences for the computational complexity . The transfer functions of these filters do not have negative lobes and thus do not exhibit phase reversal.

Examples for the rectangular support case (J=K=5) and the circular support case (R=2.5) are shown in Figure. The filter is again normalized so that Σh[j,k]=1.

$$h_{rect}[j,k] = \frac{1}{81}\begin{bmatrix} 1 & 2 & 3 & 2 & 1 \\ 2 & 4 & 6 & 4 & 2 \\ 3 & 6 & 9 & 6 & 3 \\ 2 & 4 & 6 & 4 & 2 \\ 1 & 2 & 3 & 2 & 1 \end{bmatrix} h_{circ}[j,k] = \frac{1}{25}\begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 2 & 2 & 2 & 0 \\ 1 & 2 & 5 & 2 & 1 \\ 0 & 2 & 2 & 2 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

(a) Pyramidal filter (J=K=5) (b) Cone filter (R=2.5)

Eq 4.5- Triangular filters for image smoothing

c) Gaussian filter

The Gaussian filter is a linear filter that is usually used as a smoother . The output of the gaussian filter at the moment t is the weighted mean of the input values, and the weights are defined by formula

$$\omega(\tau) = C(\sigma).\exp(-\frac{\tau}{2\sigma}) \quad ; \ \tau = -1,0,+1,....,$$

where

τ is the "distance" in time from the current moment;

σ is the parameter of the Gaussian filter;

$C(\sigma)$ is the normalization constant chosen to make the sum of all weights equal to the unit value.

The weighted mean is a measure of central tendency . The weighted mean M of a set of N values $(x_1, x_2, \ldots\ldots, x_N)$ is computed according to the following formula:

$$M(x_1, x_2, \ldots., x_N) = \frac{\sum_{i=1}^{i=N} \omega_i . x_i}{\sum_{i=1}^{i=N} \omega_i}; \omega_i \geq 0$$

Where, $(\omega_1, \omega_{2,}, \ldots., \omega_N)$ are non-negative coefficients, called "weights", that are ascribed to the corresponding values $(x_1, x_2, \ldots\ldots, x_N)$.

f you plot the values of $\omega(\tau)$ against τ , then the plot coincides with the famous bell-like curve describing the density of the gaussian distribution . This explains the word "gaussian" in the name of the filter.

The gaussian filter is completely defined by a single parameter σ. The greater the value of σ, the wider the window function $\omega(\tau)$, and, hence, the greater the degree of smoothing.

The gaussian filter provides better suppression of higher frequencies than the rectangular filter and the triangular filter .

Besides the one-dimensional gaussian filter described above, there are extensions to the case of two dimensions, say (x,y). Such two-dimensional gaussian filters are widely used in image processing.

Below a Gaussian filter is shown in 2D top view with horizontal and vertical cross sections and also in 3D view. The Gaussian function shown has a standard deviation of 10x10 and a kernel size of 35x35 pixels. Notice that a large part of the kernel for the y direction contains values very close to zero due to the low standard deviation in this direction. During the filtering process the filter kernel will be normalized so that it will not introduce a general amplification of the height values.

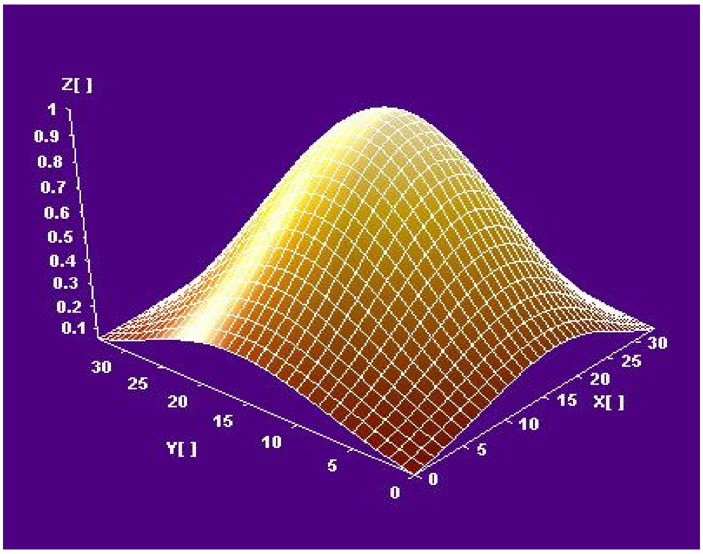


FIG 4.2: Normal distribution curve

Kernel Size

The size of the kernel should normally be selected large enough so that the kernel coefficients of the border rows and columns contribute very little to the sum of coefficients. By selecting a kernel size parameters six times the standard deviation the border parameters will be 1% or lower than the center parameter.

It is recommended to use the Auto Apply setting and having the Difference image included in the Output options such that the filter effect can be monitored in detail.

Standard Deviation

The standard deviation for a two-dimensional kernel is the radius in pixels containing 68% of the integrated magnitude of the coefficients. Increasing the standard deviation will increase the effective kernel size.

The Gaussian kernel can be used to perform an unsharp masking filter by subtracting the result from the original and can in this way serve as an ideal high pass filter.

Below is seen a filtering example where the input image is shown upper left and the filter kernel upper right while the smoothening result is monitored lower left. The lower right image is difference image between input image and the filter result. While the smooth filter result reflects the long waves (waviness) the difference image reflects the short waves of the image.

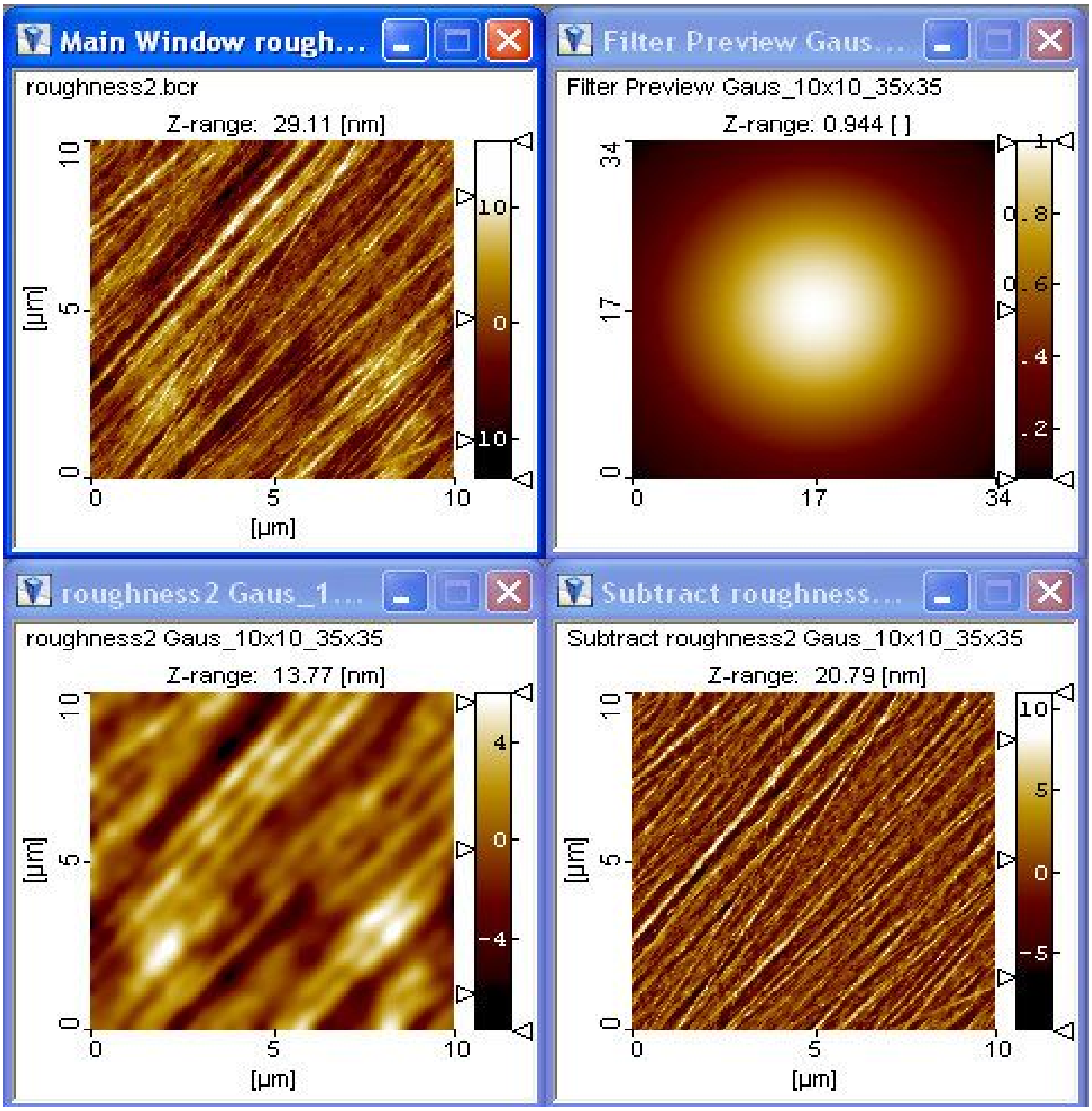


FIG 4.3: Gaussian Filter

4.4.2 Non-linear filters

In the following we give a non-exhaustive list of system nonlinearities that lead to nonlinear processing.

(i) <u>Non-Gaussian noise/signal statistics</u>. A primary example is impulsive noise filtering that frequently occurs in telecommunication channels, in TV broadcasting and in information losses in decoding or due to packet losses.

(ii) Signal-dependent noise. Multiplicative noise appears frequently during digital image acquisition. Speckle noise appears in ultrasonic images as well as in SAK. images. Film grain noise can be modeled as multiplicative noise as well. Photoelectronic digital image acquisition (e.g. by using video cameras) introduces signal-dependent noise.

(iii) Non-stationarity in signal/image statistics. Digital image statistics change from one image region to the other. Adaptive (often nonlinear) operators are used to keep track of the varying image statistics.

(iv) Signal/image acquisition nonlinearities. Several acquisition devices are highly nonlinear systems (e.g. photographic film, video cameras), whose nonlinearities are of polynomial form. Furthermore, nonlinear (usually analog) preprocessing is used sometimes in order to increase the dynamic range of the acquisition, or for compensation reasons.

(v)Transmission channel nonlinearities.Certain telecommunication channels introduce nonlinear (polynomial) distortion that produces nonlinear intersynibol interference and reduces the margin against noise. Quadratic and cubic nonlinearities provide a fairly good model for such channels.

(vi)Optimization of nonlinear objective measures**.** In several cases, nonlinear measures and/or features express fairly well certain signal/image characteristics. Image entropy is a primary example of a nonlinear measure of image information content (and tentatively its quality). Optimization of such measures leads to nonlinear digital signal processing (e.g. maximum entropy image restoration).

(vii) Nonlinearities in digital image analysis and in object recognition. Many digital image analysis operations use hard nonlinearities (e.g. maximum/minimum selection, thresholding, comparisons, quadratic nonlinearities), because image analysis leads to syinbolic descriptions that are based on decisions. For example, decisions are needed for edge detection and for region split/merge. Furthermore, shape features (e.g. skeletons, convex hulls, linear piecewise approximations) are usually nonlinear functions of the respective digital images.

Nonlinear filtering techniques are becoming increasingly important in image processing applications, and are often better than linear filters at removing noise without distorting image features. However, design and analysis of nonlinear filters are much more difficult than for linear filters. One structure for designing nonlinear filters is mathematical morphology, which creates filters based on shape and size characteristics. Morphological filters are limited to minimum and maximum operations that introduce bias into images. This precludes the use of morphological filters in applications where accurate estimation of the true gray level is necessary.

A variety of smoothing filters have been developed that are not linear. While they cannot, in general, be submitted to Fourier analysis, their properties and domains of application have been studied extensively.

a) Median filter

The median filter is a non-linear digital filtering technique, often used to remove noise from images or other signals. The idea is to examine a sample of the input and decide if it is representative of the signal. This is performed using a window consisting of an odd number of samples. The values in the window are sorted into numerical order; the median value, the sample in the center of the window, is selected as the output. The oldest sample is discarded, a new sample acquired, and the calculation repeats.

Median filtering is a common step in image processing. It is particularly useful to reduce speckle noise and salt and pepper noise. Its edge-preserving nature makes it useful in cases where edge blurring is undesirable.

Median filter is a spatial filtering operation, so it uses a 2-D mask that is applied to each pixel in the input image. To apply the mask means to centre it in a pixel, evaluating the covered pixel brightnesses and determining which brightness value is the median value. Figure presents the concept of spatial filtering based on a 3x3 mask, where I is the input image and O is the output image.

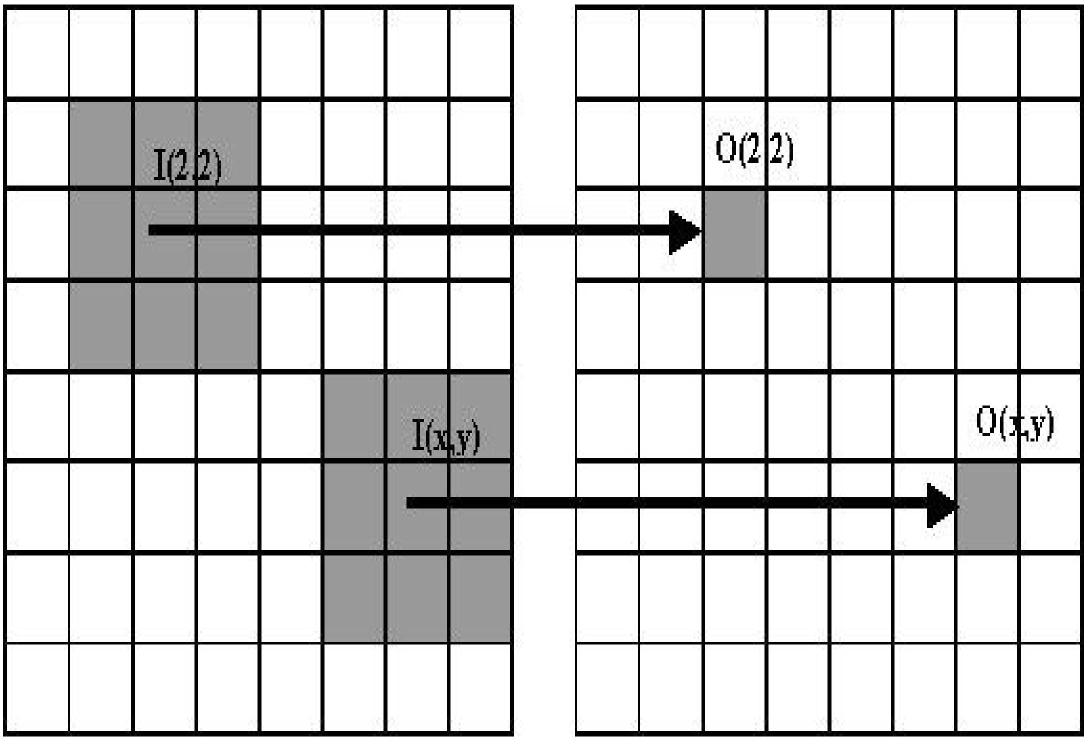
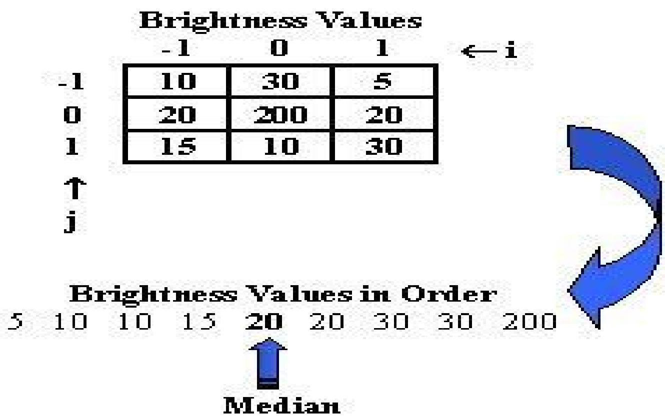


FIG 4.4: Median filter operation

The median value is determined by placing the brightnesses in ascending order and selecting the centre value. The obtained median value will be the value for that pixel in the output image. Figure shows an example of the median filter application, as in this case, habitually a 3x3 median filter is used.



Advantages over mean filter

By calculating the median value of a neighborhood rather than the mean filter, the median filter has two main advantages over the mean filter:

- The median is a more robust average than the mean and so a single very unrepresentative pixel in a neighborhood will not affect the median value significantly.
- Since the median value must actually be the value of one of the pixels in the neighborhood, the median filter does not create new unrealistic pixel values when the filter straddles an edge. For this reason the median filter is much better at preserving sharp edges than the mean filter.

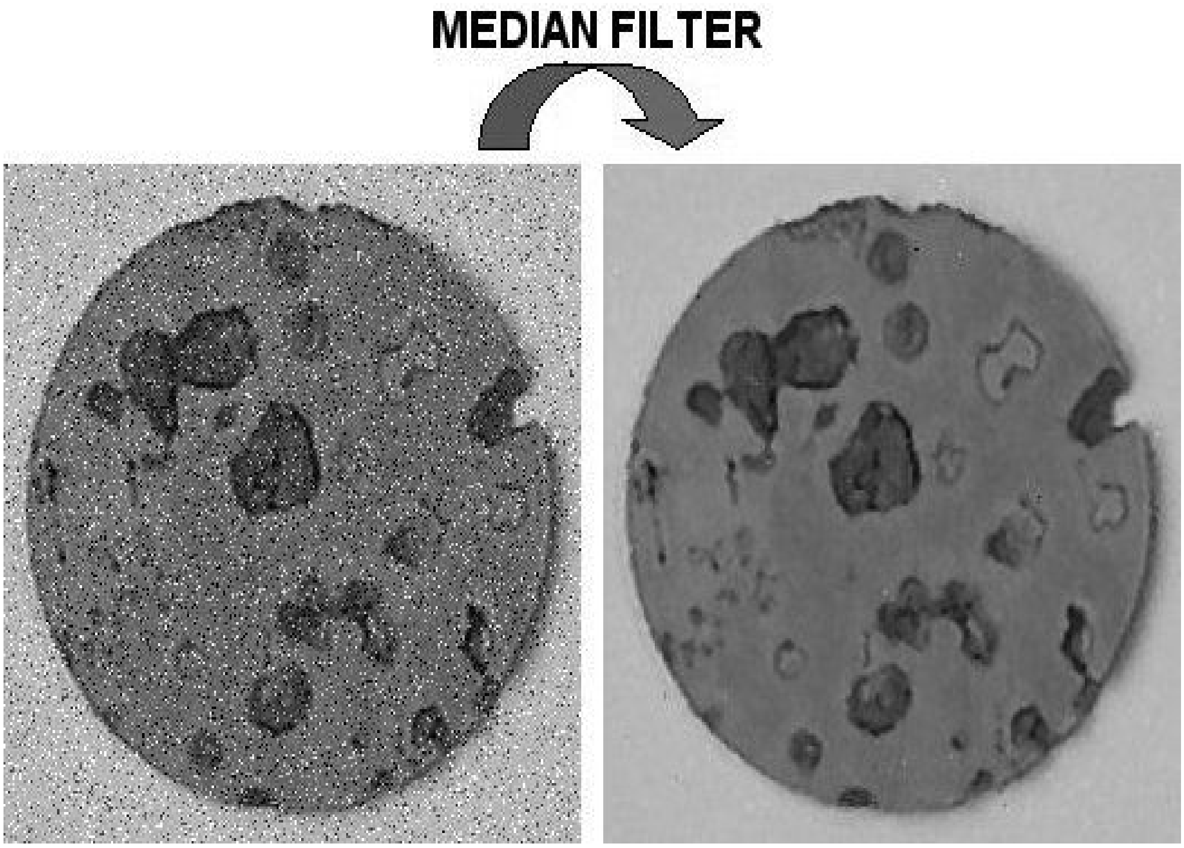


FIG 4.5: Median Filter

Operation

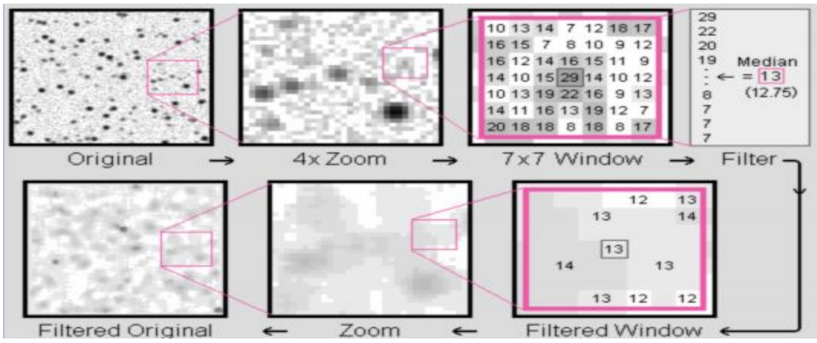


FIG 4.6: Image filtering operation

One of the major problems with the median filter is that it is relatively expensive and complex to compute. To find the median it is necessary to sort all the values in the neighborhood into numerical order and this is relatively slow, even with fast sorting algorithms such as quicksort. The basic algorithm can, however,be enhanced somewhat for speed. A common technique is to notice that when the neighborhood window is slid across the image, many of the pixels in the window are the same from one step to the next, and the relative ordering of these with each other will obviously not have changed. Clever algorithms make use of this to improve performance.

b) Mean Filter

Mean filtering is a simple, intuitive and easy to implement method of smoothing images, i.e. reducing the amount of intensity variation between one pixel and the next. It is often used to reduce noise in images.The idea of mean filtering is simply to replace each pixel value in an image with the mean (`average') value of its neighbours, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Mean filtering is usually thought of as a convolution filter. Like other convolutions it is based around a kernel, which represents the shape and size of the neighbourhood to be sampled when calculating the mean. Often a 3×3 square kernel is used, as shown in Figure 1, although larger kernels (e.g. 5×5 squares) can be used for more severe smoothing. (Note that a small kernel can be applied more than once in order to produce a similar - but not identical - effect as a single pass with a large kernel.) [http: mean]

$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$

Fig 4.7: 3×3 averaging kernel often used in mean filtering

The two main problems with mean filtering are :

- A single pixel with a very unrepresentative value can significantly affect the mean value of all the pixels in its neighbourhood.
- When the filter neighbourhood straddles an edge, the filter will interpolate new values for pixels on the edge and so will blur that edge. This may be a problem if sharp edges are required in the output.

Both of these problems are tackled by the median filter. The median filter is often a better filter for reducing noise than the mean filter, but it takes longer to compute.

4.5 Common Problems

A common problem with all filters based on all adjacent pixels is how to process the edges of the image. As the filter nears the edges, a median filter may not preserve its odd number of samples criteria. It is also more complex to write a filter that includes a method to specifically deal with the edges. Common solutions to the problem are:

- Not processing edges. With or without a crop of the image edges afterwards.
- Fetching pixels from other places in the image. Typically the other horizontal edge on horizontal edges, and the other vertical edge on vertical edges are fetched.
- Making the filter process fewer pixels on the edges.
- Comparing the filtered sample to the original sample to determine if that sample is an outlier before replacing it with the filtered one.

4.6 Current trends in non-linear filtering

It is always difficult to present the current trends of **a** broad research area in brief. It is even more difficult to predict its evolution in the decade to come.. Such trends are the following:

(i) Multichannel signal/image processing**.** Nonlinear multichannel digital filters are no straightforward extensions of their single-channel counterparts. For example the definition of multivariate data ordering possesses interesting problems in tho design of order statistics filters.
Extensions of multichannel Volterra filters could be of interest **3s** well.

(ii)Image sequence processing**.** The spatiotemporal nature of the image sequences poses new theoretical and computational problems in the design of image sequence filters. Furthermore, the human perception of image sequences puts new subjective qualitative goals in their digital
treatment.

(iii)Adaptive nonlinear filters**.** Adaptive versions have been proposed for **a** variety of nonlinear digital filter . However, the problems related to filter adaptation are far from been solved due to the nature of the adaptation problem (mainly in digital image processing), to the nature of nonlinear filter parameters (e.g. window size and shape) and to problems in adaptation convergence.

(iv)Neural filters**.** Neural networks are **a** major research trend that has influenced digital signal processing. It is believed that its merging with nonlinear filter classes will lead to useful filters that will have complex ”learning’) capabilities. For example, Volterra nonlinearities have already been used in neural networks .

4.7 Issues in filter selection

(i) Speed issues

At current time, implementing real-time filtering is pretty much out of the question. Once the kernel size is pushed upwards of a few samples, speed issues really start to kick in. For instance, convolving a 1024x1024 image with a 64x64 filter kernel, 1024x1024x64x64 (it is a 10-digit number) floating point multiplications and additions would have to be done. There is a way to slacken this situation using FFT (Fast Fourier Transform) convolution, but it won't be discussed here. There are a few *but*'s for FFT convolution as well, anyway… The moral is to always be wary when an image has to be filtered – even on today's high-end systems a large image could take more than several seconds to process using a *small* filter kernel.

(ii) Experimentation

The discussed filter kernels resulted largely from experimentation and were implemented as static filters (that means no mathematical algorithm was developed to compute them in *any* size). Coming up with such algorithms can sometimes be rather challenging.

(iii) The hidden equilibrium

It isn't that obvious, but a certain kind of "numeric balance" hides itself in filters. If the balance is shifted, the filter starts to distort the image instead of simply processing it. That is, if adding all of the values in a filter kernel together produces a value that doesn't equal 1, the filter is "numerically unbalanced".

(iv) Normal filter size

This is a fair question that can be answered in the following way: for most applications the very primitive 3x3 filter kernel is more than enough; larger filters become necessary when the output sample needs to be affected by a whole area of surrounding pixels. For instance, increasing the kernel size of the emboss/engrave filter produces an increasingly embossy/engravy effect. Implementing a large median filter (used for removing small artefacts such as speckles from the input image – not done by convolution) will yield an increasingly blurrier while smoother output image.

4.8 Filter performance parameters

To determine the efficiency of different filters , the parameters used in this work are described below :

4.8.1 Peak signal-to-noise ratio

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

The PSNR is most commonly used as a measure of quality of reconstruction in image compression etc. It is most easily defined via the mean squared error (MSE) which for two m×n monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$\text{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - k(i,j)]^2$$

The PSNR is defined as:

$$\text{PSNR} = 10.\log\frac{Max_i^{\,2}}{MSE} = 20\log_{10}\frac{Max_i}{\sqrt{MSE}}$$

Here, MAX_i is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three.

An identical image to the original will yield an undefined PSNR as the MSE will become equal to zero due to no error. In this case the PSNR value can be thought of as approaching infinity as the MSE approaches zero, this shows that a higher PSNR value provides a higher image quality. At the other end of the scale an image that comes out with all zero value pixels (black) compared to an original does not provide a PSNR of zero. This can be seen by observing the form, once again, of the MSE equation. Not all the original values will be a long distance from the zero value thus the PSNR of the image with all pixels at a value of zero is not the worst possible case.

4.8.2 Correlation

The correlation coefficient $\rho_{X,\,Y}$ between two random variables X and Y with expected values μ_X and μ_Y and standard deviations σ_X and σ_Y is defined as:

$$\rho_{X,Y} = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E((X-\mu_X)(Y-\mu_Y))}{\sigma_X \sigma_Y}$$

where E is the expected value operator and cov means covariance. Since $\mu_X = E(X)$, $\sigma_X^2 = E(X^2) - E^2(X)$ and likewise for Y, we may also write

$$\rho_{X,Y} = \frac{E(XY)-E(X)E(Y)}{\sqrt{E(X^2)-E^2(X)}} . \sqrt{\frac{1}{E(Y^2)-E^2(Y)}}$$

The correlation is defined only if both of the standard deviations are finite and both of them are nonzero. It is a corollary of the Cauchy-Schwarz inequality that the correlation cannot exceed 1 in absolute value.

The correlation is 1 in the case of an increasing linear relationship, −1 in the case of a decreasing linear relationship, and some value in between in all other cases, indicating the degree of linear dependence between the variables. The closer the coefficient is to either −1 or 1, the stronger the correlation between the variables.

If the variables are independent then the correlation is 0, but the converse is not true because the correlation coefficient detects only linear dependencies between two variables. Here is an example: Suppose the random variable X is uniformly distributed on the interval from −1 to 1, and $Y = X^2$. Then Y is completely determined by X, so that X and Y are dependent, but their correlation is zero; they are uncorrelated. However, in the special case when X and Y are jointly normal, uncorrelatedness is equivalent to independence.

A correlation between two variables is diluted in the presence of measurement error around estimates of one or both variables, in which case disattenuation provides a more accurate coefficient.

4.8.3 Signal-to-noise ratio

Signal-to-noise (SNR) measures are estimates of the quality of a reconstructed image compared with an original image. The basic idea is to compute a single number thatreflects the quality of the reconstructed image. Reconstructed images with higher metrics are judged better. In fact, traditional SNR measures do not equate with human subjective perception. Several research groups are working on perceptual measures, but for now we will use the signal-to-noise measures because they are easier to compute. Just remember that higher measures do not always mean better quality.

In engineering, signal-to-noise ratio is a term for the power ratio between a signal (meaningful information) and the background noise:

$$SNR = \frac{P_{signal}}{P_{noise}} = \left(\frac{A_{signal}}{A_{noise}}\right)^2,$$

$$SNR(db) = 10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) = 20\log_{10}\left(\frac{A_{signal}}{A_{noise}}\right)$$

where P is average power and A is RMS amplitude. Both signal and noise power (or amplitude) must be measured at the same or equivalent points in a system, and within the same system bandwidth.

Because many signals have a very wide dynamic range, SNRs are usually expressed in terms of the logarithmic decibel scale. In decibels, the SNR is, by definition, 10 times the logarithm of the power ratio. If the signal and the noise is measured across the same impedance then the SNR can be obtained by calculating 20 times the base-10 logarithm of the amplitude ratio. [http: SNR1]

CHAPTER 5

METHODOLOGY USED

5.1 Matlab software

Short for "matrix laboratory", MATLAB is a numerical computing environment and programming language. Created by The MathWorks, MATLAB allows easy matrix manipulation, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs in other languages. MATLAB is built around the MATLAB language, sometimes called M-code or simply M.

5.2 Image processing toolbox

Image Processing Toolbox is a collection of functions that extend the capability of the MATLAB numeric computing environment. The toolbox supports a wide range of image processing operations. In this work we have used MATLAB 7.0 version.

5.3 Methodology

Following steps have been performed to achieve this objective:

5.3.1 Image acquisition

The images were acquired from a radiology center. To avoid any effects on the parameters of images like change in dimensions, change in texture values due to different sources, we have taken all the images from the same source and same MRI machine. Images were taken of different body parts. The images so obtained were in DICOM format. The images were thus converted to JPEG format, so that they can easily be used in the MATLAB environment. The syntax used was:

```
I1=rgb2gray(I);
```

rgb2gray converts RGB images to grayscale by eliminating the hue and saturation information while retaining the luminance. The grayscale image is of 2D type. The images were stored in the workspace of the MATLAB software from where they can be processed.

5.3.2 Add noise

Different types of noise were added to the images like gaussian, speckle, salt & pepper, poisson, additive gaussian ,additive uniform, multiplicative gaussian and multiplicative uniform. For eg. the command used to add these noises to an image a is:

```
j=imnoise(a,'poisson');      % to add poisson noise%

j=imnoise(a,'speckle',0.01);  % to add speckle noise%

j=imnoise(a,'salt & pepper',0.01);  % to add salt & pepper noise%

j=imnoise(a,'gaussian',0.01);  % to add Gaussian noise%

j=NOISE(a,'ag', 10, 0.5);  % to add additive Gaussian noise%

j=NOISE(a,'au', 10, 0.5);  %to add additive uniform noise%
```

5.3.3 Noise filtering

The noisy images thus obtained were filtered using different filters like max, min, median, cumulative mean, bilateral and gaussian filter as shown below:

```
y=maxfilt2(j,[3 3]);  % max filter %

y=minfilt2(j,[3 3]);  % min filter %

y = rmedian(j,3,5);  % median filter %

y = cummean(j,1)  % cumulative mean filter %

y= bfilter2(a,5,2)  % bilateral filter %
```

```
y = gaussian_filter(randn(150,150),[1:150],[1:150],5); % gaussian filter %
```

5.3.4 Filter parameters

After filtering the noisy images, various parameters like PSNR, WPSNR, Correlation, SNR were calculated to determine the filter performance individually. Combination of filters were also used to achieve the desired results. All the parameters were tabulated and all the filters were analysed individually as well as in combination to find the best, second best and the worst filter in respect to noise reduction or removal.

CHAPTER 6
RESULTS & DISCUSSIONS

6.1 Results

The various parameters have been found to determine the performance of different types of filters. Five MRI scan images have been taken and different types of noise were added to it. The noisy images obtained have then been filtered using different types of filters. Then the parameters have been calculated and with this different types of filters have been compared. Depending on these values, it have been concluded which filter individually and in combination is best and which is the worst for noise reduction or removal.

Table 6.1: Results of image 1

NOISE	FILTER	PSNR	WPSNR	CORR2	SNR
GAUSSIAN	MAX	19.63	26.42	0.98	09.42
	MIN	19.58	26.40	0.98	09.19
	MEDIAN**	29.60	36.50	0.99	28.01
	CUMMULATIVE MEAN	10.19	16.19	0.73	01.66
	BILATERAL*	42.08	42.84	0.99	79.73
	GAUSSIAN***	04.14	10.69	0.02	01.54
SPECKLE	MAX	24.25	32.76	0.99	10.54
	MIN	20.31	27.16	0.99	10.64
	MEDIAN**	30.61	37.20	0.99	38.96
	CUMMULATIVE MEAN	10.30	16.29	0.73	01.66
	BILATERAL*	42.08	47.84	0.99	79.73
	GAUSSIAN***	15.23	19.37	0.53	01.12

NOISE	FILTER	PSNR	WPSNR	CORR2	SNR
SALT & PEPPER	MAX	19.70	27.53	0.97	06.20
	MIN	18.70	26.52	0.96	05.58
	MEDIAN**	46.69	59.49	0.99	135.26
	CUMMULATIVE MEAN	10.18	16.17	0.73	01.66
	BILATERAL*	42.08	47.84	0.99	79.73
	GAUSSIAN***	14.13	10.72	0.42	09.15
POISSON	MAX	18.12	26.45	0.88	02.80
	MIN	18.66	26.20	0.87	02.60
	MEDIAN**	30.00	41.58	0.98	08.63
	CUMMULATIVE MEAN	16.17	22.41	0.62	01.29
	BILATERAL*	52.53	60.74	0.99	12.77
	GAUSSIAN***	04.26	10.90	0.04	01.20
ADDITIVE GAUSSIAN	MAX	19.57	27.35	0.97	06.11
	MIN	18.72	26.53	0.96	05.57
	MEDIAN**	30.00	41.58	0.98	08.63
	CUMMULATIVE MEAN	10.18	16.17	0.73	01.66
	BILATERAL*	42.08	47.84	0.99	79.73
	GAUSSIAN***	04.03	10.63	0.01	00.12
MULTILICATIVE GAUSSIAN & MULTIPLICATIVE UNIFORM	MAX	18.13	26.48	0.88	02.80
	MIN	18.67	26.22	0.87	02.61
	MEDIAN**	08.74	14.79	0.77	01.85
	CUMMULATIVE MEAN	16.18	22.42	0.62	01.29
	BILATERAL*	52.53	60.74	0.99	12.77
	GAUSSIAN***	04.05	10.66	0.01	0.19

*** Best filter**

**** Second best filter**

***** Worst filter**

Table 6.2: Results of image 2

NOISE	FILTER	PSNR	WPSNR	CORR2	SNR
GAUSSIAN	MAX	18.99	25.38	0.98	08.49
	MIN	19.33	26.15	0.98	08.30
	MEDIAN**	27.52	36.04	0.99	16.35
	CUMMULATIVE MEAN	16.42	22.31	0.93	03.85
	BILATERAL*	37.73	43.98	0.99	45.52
	GAUSSIAN***	27.50	36.04	0.99	16.33
SPECKLE	MAX	23.12	30.87	0.98	09.24
	MIN	20.24	27.09	0.99	09.91
	MEDIAN**	28.04	36.38	0.99	18.59
	CUMMULATIVE MEAN	16.34	22.22	0.93	05.86
	BILATERAL*	37.46	43.98	0.99	45.31
	GAUSSIAN***	16.21	20.19	0.98	03.31
SALT & PEPPER	MAX	19.07	26.64	0.97	05.70
	MIN	18.82	26.51	0.96	05.63
	MEDIAN**	28.02	36.35	0.99	19.34
	CUMMULATIVE MEAN	16.46	22.35	0.93	03.85
	BILATERAL*	37.32	42.73	0.99	44.91
	GAUSSIAN***	14.25	19.21	0.98	14.31
POISSON	MAX	23.15	30.92	0.98	09.45
	MIN	21.63	28.88	0.98	09.91
	MEDIAN**	29.70	39.38	0.99	19.88
	CUMMULATIVE MEAN	16.43	22.31	0.93	03.86
	BILATERAL*	37.46	43.98	0.99	45.31
	GAUSSIAN***	21.13	19.14	0.97	16.13

NOISE	FILTER	PSNR	WPSNR	CORR2	SNR
ADDITIVE GAUSSIAN	MAX	24.13	30.91	0.98	10.01
	MIN	21.52	29.81	0.98	09.89
	MEDIAN**	28.65	38.11	0.99	18.87
	CUMMULATIVE MEAN	16.42	22.31	0.93	03.83
	BILATERAL*	37.46	43.98	0.99	45.31
	GAUSSIAN***	16.21	17.15	0.97	12.15
MULTILICATIVE GAUSSIAN & MULTIPLICATIVE UNIFORM	MAX	19.23	27.78	0.88	03.81
	MIN	19.63	27.22	0.87	03.67
	MEDIAN**	09.57	15.87	0.77	02.89
	CUMMULATIVE MEAN	17.28	23.45	0.63	02.29
	BILATERAL*	52.53	60.74	0.99	120.73
	GAUSSIAN***	05.15	10.61	0.69	01.18

*** Best filter**

**** Second best filter**

***** Worst filter**

Table 6.3: Results of image 3

NOISE	FILTER	PSNR	WPSNR	CORR2	SNR
GAUSSIAN	MAX	18.98	25.67	0.98	08.48
	MIN	19.35	26.17	0.98	07.80
	MEDIAN**	27.52	36.05	0.99	16.38
	CUMMULATIVE MEAN	16.43	22.31	0.93	03.86
	BILATERAL*	37.46	43.98	0.99	45.52
	GAUSSIAN***	27.51	36.04	0.99	16.36
SPECKLE	MAX	29.70	39.37	0.99	19.88
	MIN	20.24	27.09	0.99	09.91
	MEDIAN**	28.02	36.35	0.99	18.59
	CUMMULATIVE MEAN	16.34	22.23	0.93	03.86
	BILATERAL*	37.46	43.98	0.99	145.31
	GAUSSIAN***	16.19	20.17	0.97	15.37
SALT & PEPPER	MAX	19.11	26.66	0.97	05.72
	MIN	18.94	26.61	0.96	05.63
	MEDIAN**	28.04	35.38	0.99	19.34
	CUMMULATIVE MEAN	16.46	23.35	0.93	03.85
	BILATERAL*	37.32	42.73	0.99	44.91
	GAUSSIAN***	14.23	19.18	0.97	14.31
POISSON	MAX	23.14	30.90	0.98	09.44
	MIN	21.63	28.88	0.98	09.91
	MEDIAN**	29.70	39.36	0.99	19.90
	CUMMULATIVE MEAN	16.43	22.31	0.93	03.86
	BILATERAL*	37.46	43.98	0.99	45.31
	GAUSSIAN***	21.11	19.11	0.97	16.18

NOISE	FILTER	PSNR	WPSNR	CORR2	SNR
ADDITIVE GAUSSIAN	MAX	24.11	30.91	0.98	10.00
	MIN	21.52	28.88	0.98	09.89
	MEDIAN**	28.65	38.13	0.99	18.85
	CUMMULATIVE MEAN	16.43	22.31	0.93	04.10
	BILATERAL*	37.46	43.98	0.99	45.31
	GAUSSIAN***	16.23	17.17	0.97	12.19
MULTILICATIVE GAUSSIAN & MULTIPLICATIVE UNIFORM	MAX	18.34	26.51	0.88	02.85
	MIN	18.79	26.34	0.87	02.67
	MEDIAN**	08.87	14.82	0.77	01.89
	CUMMULATIVE MEAN	16.23	22.34	0.62	01.31
	BILATERAL*	52.53	60.74	0.99	120.77
	GAUSSIAN***	04.04	10.76	0.02	0.21

*** Best filter**

**** Second best filter**

***** Worst filter**

Table 6.4: Results of image 4

NOISE	FILTER	PSNR	WPSNR	CORR2	SNR
GAUSSIAN	MAX	18.78	25.31	0.99	10.01
	MIN	21.09	27.93	0.98	09.80
	MEDIAN**	29.28	36.26	0.99	26.14
	CUMMULATIVE MEAN	21.68	27.62	0.98	07.99
	BILATERAL*	38.62	45.96	0.99	53.40
	GAUSSIAN***	29.26	36.24	0.99	26.13
SPECKLE	MAX	37.65	46.33	0.99	52.70
	MIN	21.87	28.75	0.99	11.74
	MEDIAN**	33.61	40.96	0.99	40.56
	CUMMULATIVE MEAN	22.02	27.95	0.98	07.97
	BILATERAL*	38.62	45.96	0.99	52.60
	GAUSSIAN***	16.23	20.21	0.98	15.37
SALT & PEPPER	MAX	18.47	26.08	0.96	05.33
	MIN	20.45	28.19	0.97	06.64
	MEDIAN**	33.61	39.97	0.99	20.14
	CUMMULATIVE MEAN	21.99	27.96	0.98	07.85
	BILATERAL*	38.71	44.65	0.99	45.98
	GAUSSIAN***	16.19	20.15	0.97	15.28
POISSON	MAX	24.68	32.66	0.99	11.57
	MIN	23.34	30.66	0.99	11.56
	MEDIAN**	37.66	46.32	0.99	52.76
	CUMMULATIVE MEAN	22.19	28.11	0.98	07.95
	BILATERAL*	38.62	45.96	0.99	52.60
	GAUSSIAN***	22.01	20.19	0.98	17.21

NOISE	FILTER	PSNR	WPSNR	CORR2	SNR
ADDITIVE GAUSSIAN	MAX	26.61	31.99	0.99	12.31
	MIN	23.61	31.51	0.99	12.10
	MEDIAN**	36.15	44.15	0.99	49.91
	CUMMULATIVE MEAN	23.10	28.72	0.97	08.13
	BILATERAL*	39.65	45.86	0.99	52.61
	GAUSSIAN***	17.43	18.04	0.99	13.05
MULTILICATIVE GAUSSIAN & MULTIPLICATIVE UNIFORM	MAX	17.14	25.43	0.87	02.78
	MIN	17.56	25.19	0.87	02.59
	MEDIAN**	07.69	13.76	0.76	01.81
	CUMMULATIVE MEAN	15.21	21.40	0.63	01.29
	BILATERAL*	52.53	60.74	0.99	120.77
	GAUSSIAN***	05.11	09.46	0.11	0.21

*** Best filter**

**** Second best filter**

***** Worst filter**

Table 6.5: Results of image 5

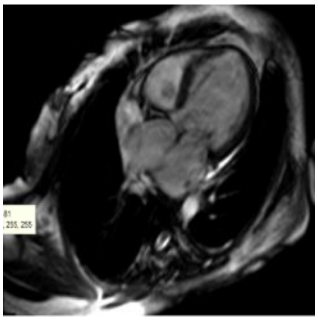
NOISE	FILTER	PSNR	WPSNR	CORR2	SNR
GAUSSIAN	MAX	13.84	20.67	0.86	03.15
	MIN	15.20	21.78	0.82	03.80
	MEDIAN**	25.77	35.20	0.96	28.01
	CUMMULATIVE MEAN	16.27	22.49	0.62	01.66
	BILATERAL*	52.53	60.74	0.99	78.72
	GAUSSIAN***	04.14	10.69	0.02	01.54
SPECKLE	MAX	18.22	26.63	0.89	31.57
	MIN	18.84	26.37	0.87	01.95
	MEDIAN**	29.19	39.86	0.98	38.96
	CUMMULATIVE MEAN	16.17	22.41	0.62	01.66
	BILATERAL*	52.53	60.74	0.99	79.73
	GAUSSIAN***	04.13	10.65	0.04	01.56
SALT & PEPPER	MAX	15.20	23.56	0.72	01.62
	MIN	17.97	26.08	0.79	01.98
	MEDIAN**	30.99	44.21	0.98	09.68
	CUMMULATIVE MEAN	16.15	22.48	0.61	01.25
	BILATERAL*	36.13	46.76	0.88	34.17
	GAUSSIAN***	04.13	10.72	0.02	00.15
POISSON	MAX	18.12	26.45	0.88	02.80
	MIN	18.66	26.20	0.87	02.60
	MEDIAN**	30.00	41.58	0.98	08.63
	CUMMULATIVE MEAN	16.17	22.41	0.62	01.29
	BILATERAL*	52.53	60.74	0.99	120.77
	GAUSSIAN***	04.26	10.90	0.04	00.20

NOISE	FILTER	PSNR	WPSNR	CORR2	SNR
ADDITIVE GAUSSIAN	MAX	18.13	26.48	0.88	02.80
	MIN	18.67	26.22	0.87	02.61
	MEDIAN**	30.00	41.58	0.98	08.63
	CUMMULATIVE MEAN	16.18	22.42	0.62	01.29
	BILATERAL*	52.53	60.74	0.99	120.77
	GAUSSIAN***	04.03	10.63	0.01	0.12
MULTILICATIVE GAUSSIAN & MULTIPLICATIVE UNIFORM	MAX	18.13	26.48	0.88	02.80
	MIN	18.67	26.22	0.87	02.61
	MEDIAN**	08.74	14.79	0.57	01.15
	CUMMULATIVE MEAN	16.18	22.42	0.62	01.29
	BILATERAL*	52.53	60.74	0.99	120.77
	GAUSSIAN***	04.05	10.66	0.01	00.19

*** Best filter**

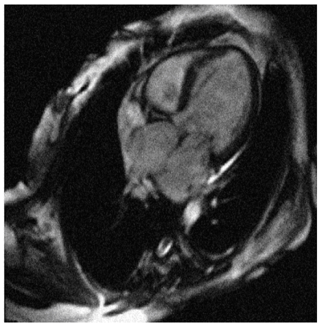
**** Second best filter**

***** Worst filter**



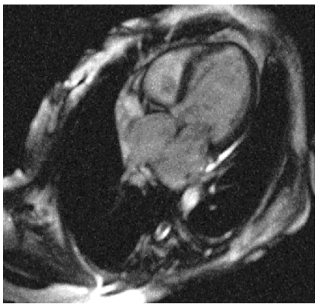
ORIGINAL IMAGE

(a)



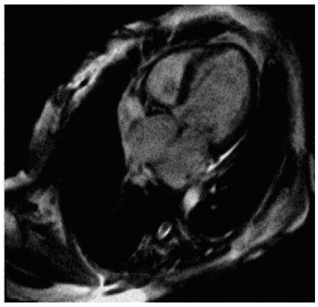
GAUSSIAN NOISE

(b)



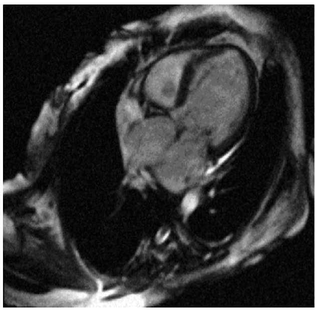
MAX FILTER

(c)



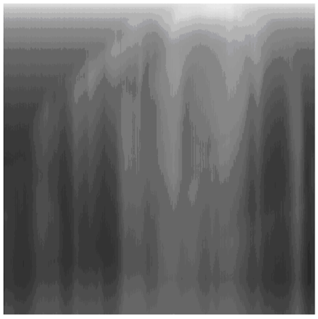
MIN FILTER

(d)



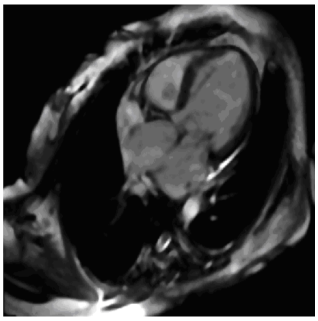
MEDIAN FILTER

(e)



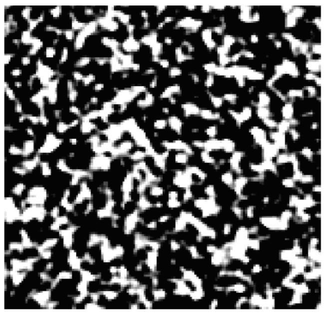
CUMMULATIVE MEAN FILTER

(f)



BILATERAL FILTER

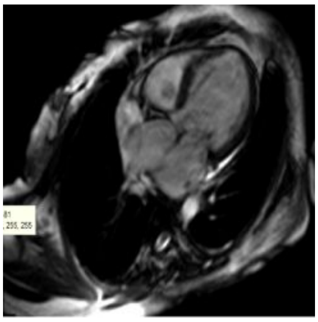
(g)



GAUSSIAN FILTER

(h)

Fig 6.1(a, b, c, d, e, f, g, h): Filtering gaussian noise from image 1

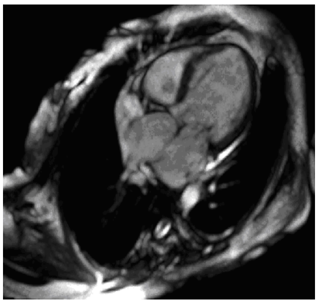


ORIGINAL IMAGE

(a)

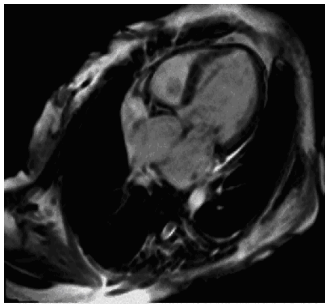
SPECKLE NOISE

(b)



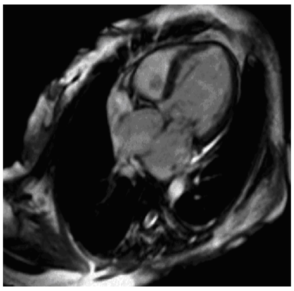
MAX FILTER

(c)



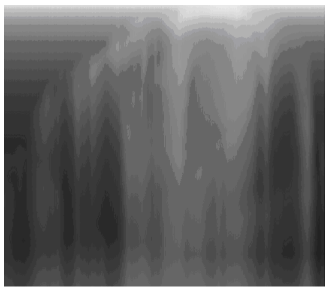
MIN FILTER

(d)



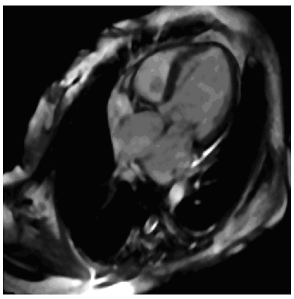
MEDIAN FILTER

(e)



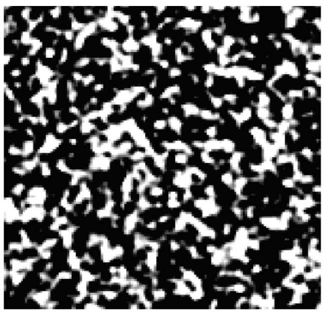
CUMMULATIVE MEAN FILTER

(f)



BILATERAL FILTER

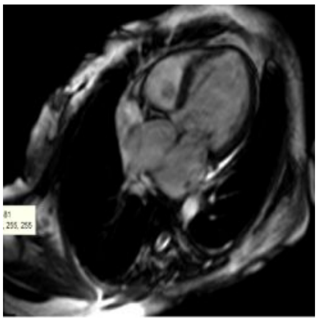
(g)



GAUSSIAN FILTER

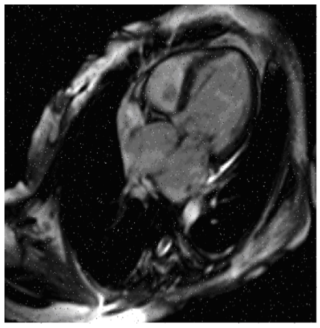
(h)

Fig 6.2(a, b, c, d, e, f, g, h): Filtering poisson noise from image 1



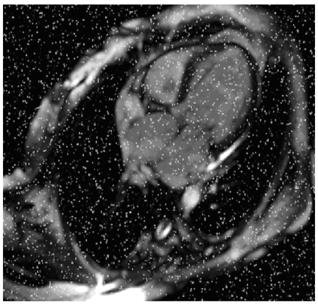
ORIGINAL IMAGE

(a)



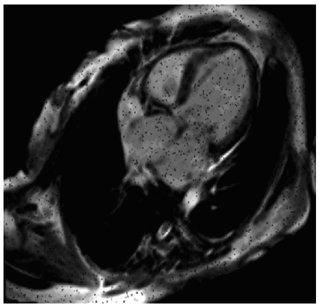
SALT & PEPPER NOISE

(b)



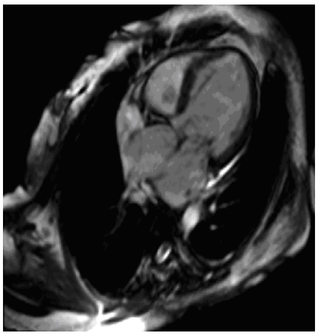
MAX FILTER

(c)



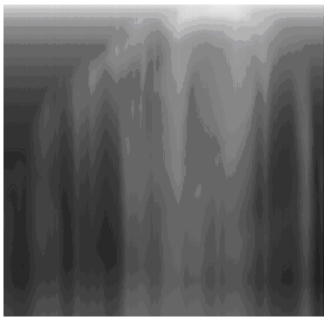
MIN FILTER

(d)



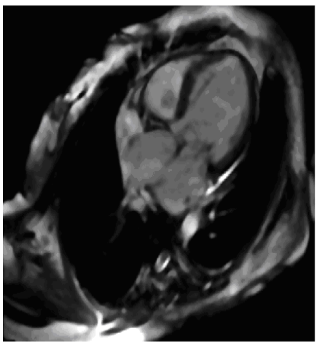
MEDIAN FILTER

(e)



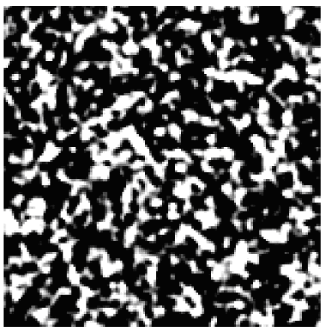
CUMMULATIVE MEAN FILTER

(f)



BILATERAL FILTER

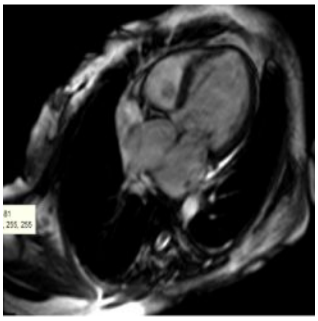
(g)



GAUSSIAN FILTER

(h)

Fig 6.3(a, b, c, d, e, f, g, h): Filtering salt & pepper noise from image 1

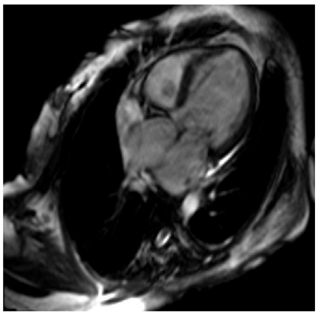


ORIGINAL IMAGE

(a)

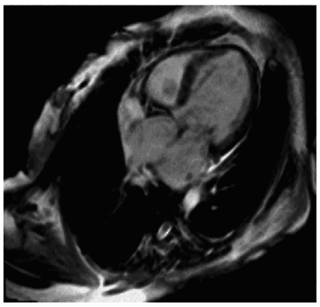
POISSON NOISE

(b)



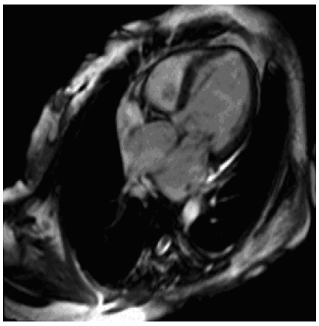
MAX FILTER

(c)



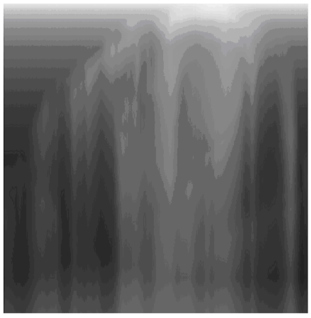
MIN FILTER

(d)



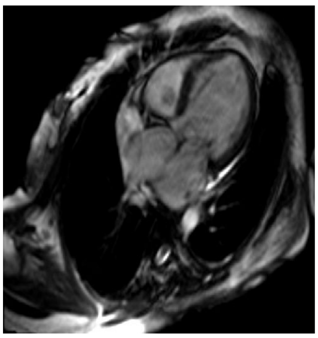
MEDIAN FILTER

(e)



CUMMULATIVE MEAN FILTER

(f)



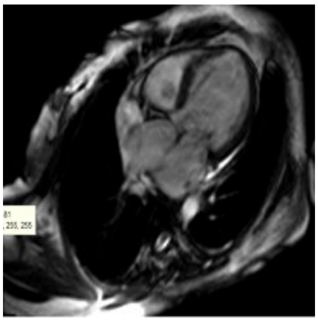
BILATERAL FILTER

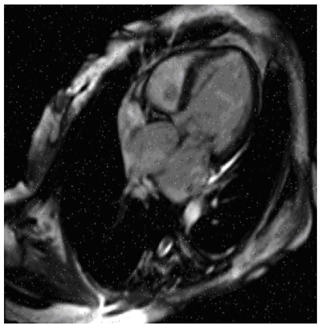
(g)

GAUSSIAN FILTER

(h)

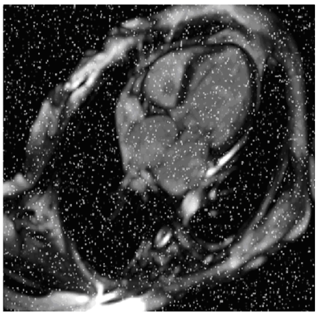
Fig 6.4(a, b, c, d, e, f, g, h): Filtering poisson noise from image 1

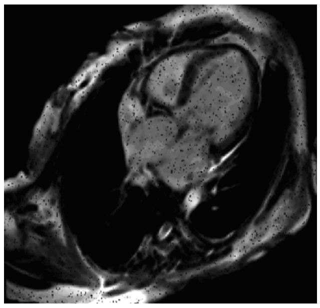




ORIGINAL IMAGE **ADDITIVE GAUSSIAN NOISE**

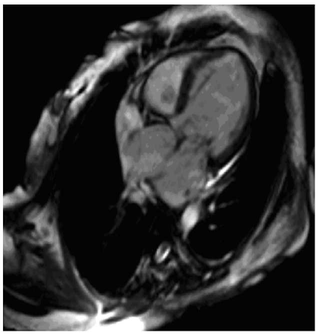
(a) **(b)**





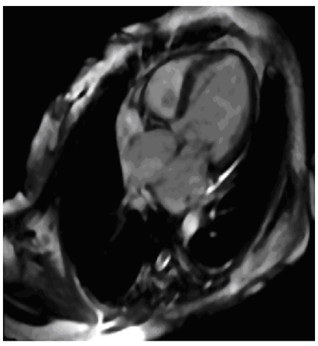
MAX FILTER **MIN FILTER**

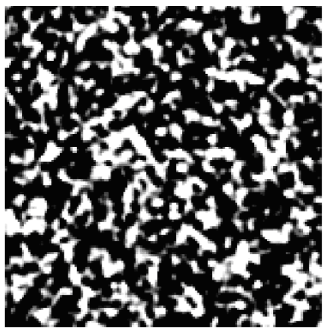
(c) **(d)**



MEDIAN FILTER **CUMMULATIVE MEAN FILTER**

(e) **(f)**

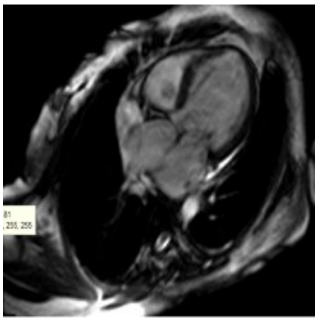




BILATERAL FILTER **GAUSSIAN FILTER**

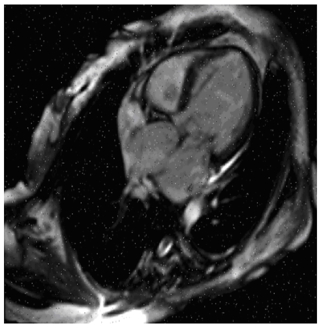
(g) **(h)**

Fig 6.5(a, b, c, d, e, f, g, h): Filtering additive Gaussian noise from image 1



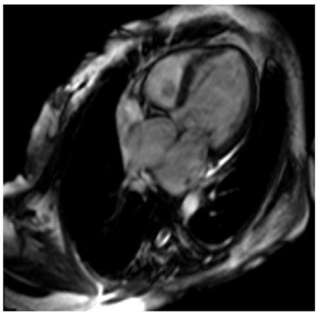
ORIGINAL IMAGE

(a)



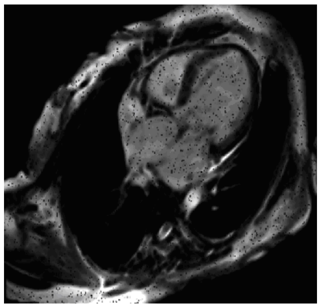
MULTIPLICATIVE UNIFORM NOISE

(b)



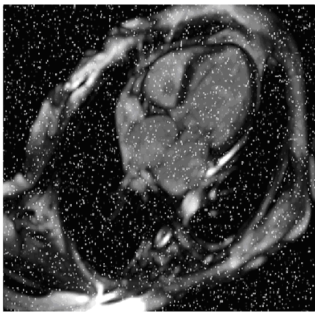
MAX FILTER

(c)



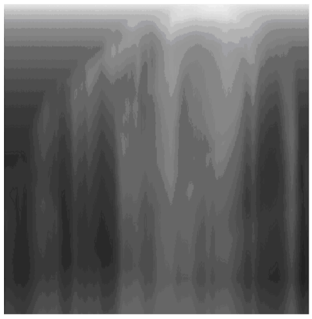
MIN FILTER

(d)



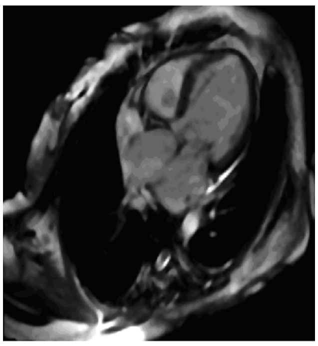
MEDIAN FILTER

(e)



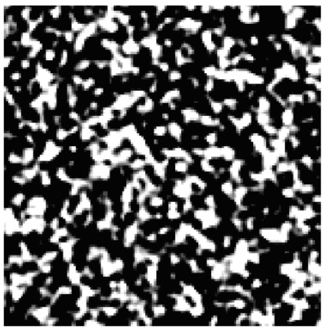
CUMMULATIVE MEAN FILTER

(f)



BILATERAL FILTER

(g)



GAUSSIAN FILTER

(h)

Fig 6.6(a, b, c, d, e, f, g, h): Filtering multiplicative uniform noise from image 1

From the results obtained in table 6.1 to 6.5 we have determined the best, second best and the worst filter used to remove or reduce noise. This information is tabulated in table 6.6.

NOISE	**BEST FILTER**	**SECOND BEST FILTER**	**WORST FILTER**
GAUSSIAN	BILATERAL	MEDIAN	GAUSSIAN
SPECKLE	BILATERAL	MEDIAN	GAUSSIAN
SALT & PEPPER	MEDIAN	BILATERAL	GAUSSIAN
POISSON	BILATERAL	MEDIAN	GAUSSIAN
ADDITIVE GAUSSIAN	BILATERAL	MEDIAN	GAUSSIAN
MULTIPLICATIVE GAUSSIAN	BILATERAL	MAX	GAUSSIAN

Table 6.6: Performance analysis of filters

It has been determined that the best filter is the bilateral filter and the second best is median filter for removing or reducing noise from images. The worst performance is shown by Gaussian filter.

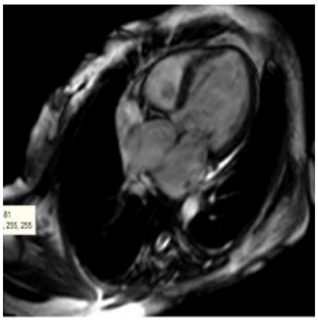
6.2 Combination of filters

Now we have used the combination of best and the second best filter to achieve better results. Firstly we have chosen the combination of median filter and bilateral filter. Secondly we have chosen the combination of bilateral and median filter.

NOISE	PSNR	WPSNR	CORR2	SNR
GAUSSIAN	30.72	36.83	0.99	44.93
SPECKLE	31.10	37.18	0.99	54.64
SALT & PEPPER	40.51	47.01	0.99	66.47

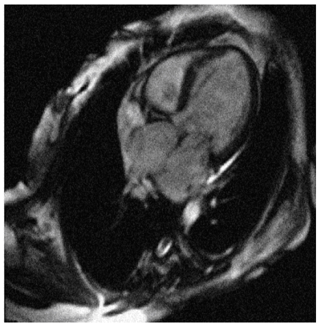
POISSON	35.38	41.57	0.99	61.01
ADDITIVE GAUSSIAN	02.97	08.99	0.63	01.33
MULTILICATIVE GAUSSIAN & MULTIPLICATIVE UNIFORM	02.99	08.99	0.31	0.68

Table 6.7: Combination of median & bilateral filters



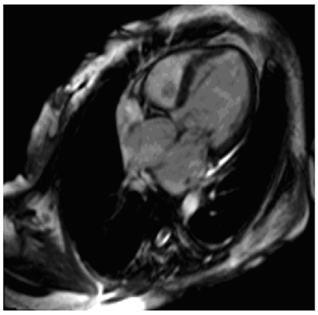
ORIGINAL IMAGE

(a)



GAUSSIAN NOISE

(b)



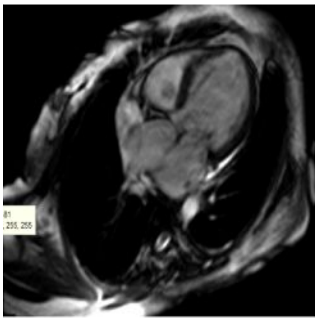
COMBINATION OF MEDIAN & BILATERAL FILTERS

(c)

Fig 6.7(a, b, c): Noise filtering using combination of median & bilateral filters

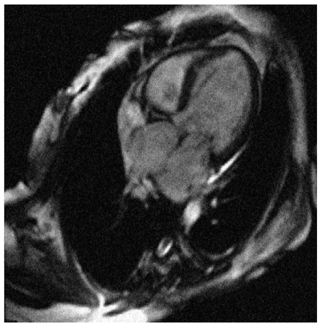
Table 6.8: Combination of bilateral & median filters

NOISE	PSNR	WPSNR	CORR2	SNR
GAUSSIAN	20.17	32.78	0.96	25.81
SPECKLE	21.31	34.23	0.97	35.72
SALT & PEPPER	25.19	38.65	0.99	26.54
POISSON	21.36	36.14	0.98	38.34
ADDITIVE GAUSSIAN	02.89	06.71	0.63	00.99
MULTIPLICATIVE GAUSSIAN & MULTIPLICATIVE UNIFORM	02.87	06.73	0.28	00.57



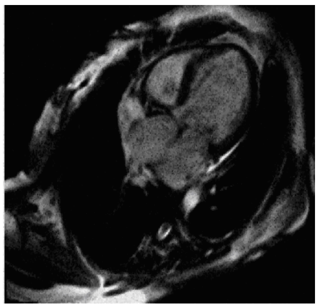
ORIGINAL IMAGE

(a)



GAUSSIAN NOISE

(b)



COMBINATION OF BILATERAL & MEDIAN FILTER

(c)

Fig 6.8(a, b, c): Noise filtering by combination of bilateral & median filter

6.3 Conclusion

It have been concluded that amongst all type of filters, bilateral filter is the best filter and median filter is the secong best except in extreme cases bilateral filter is the second best filter. So bilateral filter have been declared as universal filter for noise reduction or removal. It have also been concluded that combination of filters are not giving better results as compared to individual filters.

6.4 Future scope

The study presented here is a small part of noise reduction in MRI scan images. Here, a small number of images are taken which are not sufficient to statistically prove the results of this thesis work. In order to arrive to definite conclusions, it is necessary to study a larger number of images.

All the images taken in this study are from the same MRI scan machine. To take this study a step further, images from different MRI scan machines can be taken to study the effects of taking data from different sources.

Further combination of filters can be taken to obtain better results and more than one noise can be added to a single image and then filter parameters can be determined. Other filters can be applied to the same process. Also, other images like CT, Ultrasound, X ray images etc. can also be taken and effects of various parameters can be studied on them.

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