QUALITY ASSESSMENT ON MEDICAL IMAGE DENOISING ALGORITHM:
DIFFUSION AND WAVELET TRANSFORM FILTERS

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An image is often corrupted by noise during its acquisition and transmission process. Removing noise from the original image is still a challenging problem for researchers. Medical image carries very important information about human organs that were used for diagnosis. This project proposed techniques that will remove the noise while keeping the important information or details of the image unaffected. Image enhancement was implemented in this project to improve the quality of the images. The proposed techniques for medical image denoising are diffusion filter and discrete wavelet transform. Image quality after denoising was measured in this project based on Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and the Structural Similarity Index Metric (SSIM). From the obtained results, the images were enhanced and their quality quietly high. From the measurement parameters of image quality, diffusion filter resulted in high level of image quality as given by structural similarity index metrics. The noise has been totally removed under the proposed algorithm and it can be concluded that diffusion filter resulted in removing the noise and maintaining the important details of the images. The images remained unaffected when increasing the contrast.
ABSTRAK

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<tr>
<td>$\mu$</td>
<td>Edge Estimate</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Threshold</td>
</tr>
<tr>
<td>$\Theta$</td>
<td>The Convolution Operation</td>
</tr>
<tr>
<td>$A_j$</td>
<td>The Low Frequency</td>
</tr>
<tr>
<td>$W_j$</td>
<td>The High Frequency</td>
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<tr>
<td>$\sigma$</td>
<td>Variance</td>
</tr>
<tr>
<td>$dB$</td>
<td>Decibel</td>
</tr>
<tr>
<td>$k$</td>
<td>Edge Magnitude Parameter</td>
</tr>
<tr>
<td>IT</td>
<td>Information Technology</td>
</tr>
<tr>
<td>CT</td>
<td>Computed Tomography</td>
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<tr>
<td>MRI</td>
<td>Magnetic Resonance Imaging</td>
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<td>US</td>
<td>Ultrasound</td>
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<td>SPECT</td>
<td>Single Photon Emission Computed Tomography</td>
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<td>PET</td>
<td>Positron Emission Tomography</td>
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<td>SNR</td>
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<td>Mean Square Error</td>
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<td>Peak-Signal-to-Noise Ratio</td>
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<td>SSIM</td>
<td>Structural Similarity Index Metric</td>
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<tr>
<td>PDF</td>
<td>Probability Density Function</td>
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<td>AWGN</td>
<td>Additive White Gaussian Noise</td>
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<td>PDE</td>
<td>Partial Differential Equation</td>
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<td>Discrete Wavelet Transform</td>
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CHAPTER 1

INTRODUCTION

1.1 Background

Medical information composing of clinical data, images, and other physiological signals, has become an essential part of a patient’s care, whether during the screening, diagnostic stage or treatment phase. Over the past three decades, rapid developments in Information Technology (IT) and medical instrumentation have facilitated the development of digital medical imaging. This development has mainly concerned Computed Tomography (CT), Magnetic Resonance Imaging (MRI), different digital radiological processes of vascular, cardiovascular and contrast imaging, mammography, diagnostic ultrasound imaging, nuclear medical imaging with Single Photon Emission Computed Tomography (SPECT), and Positron Emission Tomography (PET) (Prudhvi & Venkateswarlu, 2012). All these processes have produced ever-increasing quantities of images. These images are different from typical photographic images, primarily because they reveal internal anatomy as opposed to an image of the surface. Specificities of medical images in natural monochromatic or colour images, the pixel intensity of the image corresponds to the reflection coefficient of natural light.

Image denoising is a procedure in digital image processing, aiming at the deletion of noise and is still a difficult problem for researchers (Rathor et al., 2012). In the medical field, especially in MRI, images are typically corrupted with noise, which hinder the medical diagnosis based on these images. Noise degrades the quality of images, suppressing structural details, thus create difficulties in medical diagnosis. Therefore, in medical image, de-noising it is necessary to remove the
noise while preserving important features. There have been several denoising techniques like Wiener filter, Median filter, Average filter, and Wavelet Thresholding; Principle Component Analysis (PCA), Independent Component Analysis (ICA) and Topographic ICA. Each technique has its assumptions, merits, and demerits. The prime focus of this project is to perform comparative studies of diffusion filter and wavelet transform and to evaluate their performance in denoising data. The main advantages of wavelet transform over other existing signal processing techniques are its space-frequency localization and multi-scale view of the components of a signal, also to identify spatial structure in transect data. Furthermore, there must be a suitable representation of the data in order to facilitate any analysis procedures. By using transformation or decomposition techniques, it can achieve and reach the maximum goal of the signals set of basic functions prior to processing in the transform domain. Digital images are subject to a wide variety of distortions during acquisition, processing, storage, transmission, and reproduction, which may result in a degradation of visual quality. So, measurement of image quality is very important to numerous image processing applications.

1.2 Problem Statement

In any images denoising algorithm, it is important that the denoising process has no bluffing, distortion effect and interference with the signal or image. Medical images carry important information that is needed for diagnosis. Medical images are exposed to white Gaussian noise during its acquisition and transmission, where its power is uniformly dispersed over the spectral and spatial places, and this makes it hard for the doctor to diagnose the disease (Rani et al., 2012). Some filters have been designed to remove noise and keep the important information of the image unaffected. However, performance evaluations of these filters are still needed to evaluate the filter in removing noise from medical image.

1.3 Motivation

Medical images carry very important information about our body organs and structures. The acquired tools used to collect the medical images usually produce some noises depending on the imaging modality. Image enhancement and denoising
is needed for the diagnosis of patients. Designing a filter or building up an algorithm that will remove the noise and enhance the contrast of the medical image is very important. Image denoising with wavelet transform become an interesting area of research in the recent years since it has the property of multi-resolution. Furthermore, the properties of wavelet transform make it very sufficient to denoising the images with less degradation compared to other digital filters. Different images with a different scale can be obtained through wavelet transform even though there is some of the high-frequency information hidden in a high-frequency sub-images of the wavelet transform. Therefore, to enhance a medical image efficiently, more images should be obtained with high frequency information. On other ways, diffusion filter has received much deliberation and experienced important developments with promising results and applications in various specific domains. This technique can improve the image by lessening density inside unwanted objects in the image without losing much information and reinforce contrast of the edges of the image (Wang et al., 2010). As a result, it is proposed for denoising medical images that will result in high quality. Some filter results in blurring effect or in reducing the data of the images while these data are one of the interests. Therefore, image quality assessment is needed to evaluate the filtering algorithm. The goal of image quality assessment is to measure the strength of the perceptual similarity between denoised images and reference images.

1.4 Objectives of the Research

Based on research background and the related issues, the objectives of this research have been formulated as follows:

(i) To denoise medical images using diffusion filter and wavelet transform techniques.

(ii) To evaluate the performance of diffusion and wavelet filtering in removing noise from medical images by measuring Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), Peak-Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index Metric (SSIM) to further validate their performance on removing noise of medical images.

(iii) To compare the performance of the two filters for denoising medical images.
1.5 Scope of the Research

The research will be started using medical images from MedPix (MedPix, 2000), followed by pertaining filtering algorithm by diffusion filter and wavelet transform, performing quality evaluation of the two filters on the denoised images, and finally, validation of which filtering algorithm work better.

1.6 Significant of the Research

The significant of this research are formulated as follows:

(i) Medical images are used for diagnosis purpose.

(ii) Medication is done based on the result shown in the imaging system as a result is needed to improve its quality.

1.7 Outline of the Research

In this project, the work is divided into five chapters, starting from introduction and ending with the conclusion.

Chapter 1 introduces general information about the project and discusses some of the advantages and significance of the proposed project. General introduction to image quality measured are discussed and some image quality assessment measured are proposed in this project for the evaluation of the design algorithms. The problem statement is defined properly and the proposed solutions to the existing problems are suggested, but details will be discussed in Chapter 3.

Chapter 2 introduces several imaging modalities, types of noise, image denoising techniques, and several image quality assessments are measured. Many algorithms are discussed in this chapter and several works have been reviewed and used in this chapter as literature review for the whole project. Furthermore, limitations of the previous methods were introduced and based on that; two algorithms are proposed in this project.

Chapter 3 introduces several image enhancement techniques and explanations on their mathematical representations are illustrated and discussed. The proposed methods are discussed in details and their advantages are mentioned and compared with existing algorithms. A new image quality measure is proposed, where the
structural similarity index metric is one of the best measures of image quality and it is used for the evaluation of the proposed algorithms in denoising medical images.

Chapter 4, discuss the obtained results from the proposed filters and shows the analysis of both algorithms in the denoised images. This chapter also knowledge any of the filters proposed works best at removing Gaussian noise from medical image through the results obtained by several image quality assessments.

Chapter 5, summarize and conclude the project and propose a future work on the comparison of the denoising techniques. Besides, the complexity of the algorithms can be measured according to the CPU computing time flops.
CHAPTER 2

LITERATURE REVIEW

This chapter introduces medical imaging, image quality assessment methods and image denoising techniques. In this chapter, general overview and background studies are introduced, followed by discussion on the literatures related to the field, and finally, summary of the importance of the proposed algorithms for solving the drawback by previous methods.

2.1 Medical Image

Medical images obtained from Magnetic Resonance Imaging (MRI), Computed Tomography (CT) and Ultrasound imaging (US) are the most common tools for diagnosis. These images are often subjected to random noise that occur during the process of obtaining images. The attendance of noise not only produces unwanted visual quality, but also lowers the visibility of low-contrast objects. Thus, the medical imaging analysis considered image denoising as one of the basic tasks (Ke Lu et al., 2012).

2.2 Medical Image Processing

The image processing is now a critical component in science and technology. The influence and effect of digital images on current society is astonishing. Progress in computerized medical image reconstruction and related developments has propelled medical imaging into one of the most important sub-fields of scientific imaging, especially in analysis methods and computer-aided diagnosis. In medical image
processing, the area of interest is being raised. It comprises an extensive range of methods and techniques, initiating with the acquisition of images by exploiting specialized devices, image enhancement and analysis, to 3D model reconstruction from 2D images captured by the device (Sudha et al., 2009). The captured or digitized image will undergo the process of segmentation and extraction of important information before further processed in medical imaging for diagnosis.

Medical images are usually of low contrast and due to various acquisitions, as well as display devices because of application of diverse types of quantization or reconstruction and enhancement algorithms. Image processing techniques have made it feasible to extract meaningful information from medical images with less degradation.

The main objective of medical imaging is to acquire a high resolution image with as much detail as possible for the sake of diagnosis, analysis of disease, and other applications used for. To achieve the finest possible diagnoses, it is necessary that medical images be clear and free of noise and artifacts. Noise removal is one of the major challenges in the study of medical imaging (Buades et al., 2005). Consequently, they could mask and blur important but delicate features in the images, which reflect that the noise in medical images creates a problem. Therefore, medical image processing and analyzing focuses on the structural and functional.

2.3 The Noise

Whatever the noise type and characteristics is, it is considered as undesired contents in a desired pattern or image. The categorization of noise relies mainly on the characterizing probabilistic provision. Usually, the noise hides some information about the images and it makes it difficult for the doctors to diagnose. Image diagnosis is always done after applying image enhancement and denoising techniques to the original images.

There are many types of noises occurs in medical images during acquisition and transmission. Mostly occurred noise are Gaussian noise, Speckle noise, salt and pepper noise, Rician noise, Brownian noise and so on. The Rician noise corrupts the MRI images while the Speckle noise corrupts the ultrasound images. When an electron is generated thermally at the sensor site, dark current noise is introduced in an image. Therefore, its sensor is temperature dependent (Kaur & Sharma, 2013).
This present the essential description of the most commonly present types of noise that corrupts the images during its acquisition or transmission process.

### 2.3.1 The White Noise

The white or Gaussian noise is the most common type of noise where its power is uniformly dispersed over the spectral and spatial spaces and its mean is zero (Rani et al., 2012). This type of noise has a probability density function (PDF) of the normal distribution (also known as Gaussian distribution). It most commonly presents as additive noise to be called additive white Gaussian noise (AWGN) as described by previous researchers. Gaussian noise generates a series of noise having a Gaussian normal distribution function according to the probability density function equation.

### 2.3.2 Poison Noise

The nonlinear response of the image detectors and recorders generate poison noise. This noise is image data dependent. This expression arises because detection and recording processes include random electron emission having a Poisson distribution with a mean response value. Since the mean and variance of a Poisson distribution are equal, the image dependent term has a standard deviation if it is assumed that the noise has a unity variance (Kaur & Kaur, 2013).

### 2.3.3 Speckle Noise

All conventional medical images B-mode ultrasonic have speckle noise and can be an unwanted property since it masks small but diagnostically significant features (Chen et al., 2003). In general, speckle noise commonly referred to data dropout noise. This noise is caused by errors in data transmission as given by the literature. The corrupted pixels are either set to the maximum value, which is something like a snow in the image or have single bits flipped over. Speckle noise follows a gamma distribution function.
Image enhancement is basically improving the interpretability or perception of information in images for human viewers and providing better input for other automated image processing techniques. The principal objective of image enhancement is to modify attributes of an image to make it more suitable for a given task and a specific observer. One or more attributes of the image are modified during this process. The choice of attributes and the way they are modified are specific to a given task. Furthermore, observer-specific factors such as the human visual system and the observer's experience or talent will introduce a great deal of subjectivity into the choice of image enhancement methods. Many existing techniques enhance a digital image without spoiling it. Image enhancement methods can broadly be divided into the following two categories (Maini & Aggarwal, 2010):

(i) Spatial Domain Methods: the spatial domain techniques deal with the image pixels. The pixel values are manipulated to achieve desired enhancement.

(ii) Frequency Domain Methods: the image is first transferred into frequency domain in this category. It means that the Fourier Transform of the image is computed first. All the enhancement operations are performed on the Fourier transform of the image, and then, the Inverse Fourier transform is performed to get the resultant image. These enhancement operations are performed in order to modify the image brightness, contrast or the distribution of the gray levels. As a consequence, the pixel value (intensities) of the output image will be modified according to the transformation function applied to the input values.

Image enhancement is applied in every field where images are ought to be understood and analyzed.

2.4 Grey Level Slicing

Grey level slicing is the spatial domain equivalent to band-pass filtering. A grey level slicing means transforming image $f$ into image $g$ using $T$, where $T$ is the transformation operator. The values of pixels in images $f$ and $g$ are denoted by $r$ and $s$, respectively. As given, the pixel values of $r$ and $s$ are related by the expression:
\[ s = T(r) \]  

(2.1)

where \( T \) is a transformation that maps a pixel value \( r \) into a pixel value \( s \).

However, the results of this transformation are mapped into the grey scale range of digital images. Therefore, the results are mapped back into the range of \([0, L-1]\), where \( L=2^k \), \( k \) being the number of bits in the image considered. For instance, for an 8-bit image, the range of pixel values will be \([0, 255]\). A digital gray image can have pixel values in the range of 0 to 255 (Maini & Aggarwal, 2010).

### 2.4.2 Median Filter

Median filtering is similar to the mean or averaging filter since they produce pixel, this is set to an "average" of the pixel values in the surrounding region of the corresponding input pixel. In median filtering, the importance of an output pixel is determined by the median of the surrounding region of pixels rather than the mean. Among the advantages of median filter is that the median is much less sensitive than the mean to critical values. Furthermore, median filtering is able to remove these outliers without decreasing the amount of sharpness of the image (Arastehfar et al., 2013). In median filter, the size of the neighbourhood used for filtering is 3-by-3 as shown in Figure 2.1.

![Median Filter Representation](image-url)
2.5 Image Denoising Techniques

Image denoising is done by filtering or designing tools to remove the noise. Filtering divide in broad categories depends on its operation or efficiency. Denoising of images in medical science is still a challenging problem up to today. There are so many techniques and algorithms published, where each has their own assumptions limitations and advantages. Common methods of image denoising are spatial domain and transform domain. The linear filter such as Weiner and non-linear threshold filtering, wavelet coefficient model, non-orthogonal wavelet transform, wavelet shrinkage, anisotropic filtering and trilateral filtering are used in denoising. Examples of spatial filtering are mean filtering and Gaussian filtering. The results obtained by linear filters are not good because they destroy the fine details and lines and blur the sharp edges of the images. Bilateral filter is used recently to denoise the images since it work effectively with high frequency areas, but it fails to work at low frequency. In fact, it fails to remove salt and pepper noise and gives low performance to remove speckle noise. It can be concluded that each technique or filter or algorithm has its own advantages and limitations or drawbacks. Up to now, there are so many filters for medical image denoising but medical image denoising is still a challenging problem (Kaur & Sharma, 2013).

2.5.1 Diffusion Filter Technique

Diffusion filter is a new proposed filter, hence rarely used in image processing. The elegant property of the technique is that it can enhance images by reducing unwanted intensity variability within the objects in the image without losing much information and enhance the contrast of the edges (Wang et al., 2010).

2.5.1.1 Nonlinear Diffusion Filtering Algorithm

The nonlinear diffusion filtering operation is governed by the following nonlinear partial differential equation (PDE):

\[ f_t(x, y) = div[c(x, y) \nabla f_t(x, y)] \]  \hspace{1cm} (2.2)
where \( f_t(x, y) \) is the initial noisy image at time \( t \) and the solution of the above PDE iteratively yields a filtered version which can be considered as the denoised image (Boguslaw et al., 2012). In equation 2.2, \( c(x, y) \) is the diffusion coefficient, controlling the diffusion amount and is typically described by a diffusivity function:

\[
c(x, y) = g(|\mu(x, y)|) = \frac{1}{1 + \left(\frac{|\mu(x, y)|}{\gamma}\right)^2} \tag{2.3}
\]

where \(|\mu(x, y)|\) is the edge estimate at pixel \((x, y)\), usually approximated by a gradient magnitude operator, and \(\gamma\) is the edge threshold parameter. The diffusivity function \(g(|\mu|)\) is a nonnegative monotonically decreasing function and depending upon the value of the edge threshold, \(\gamma\), encourages homogenous regions with reduced noise while preserving the edges (Gottschlich & Scho, 2012). The nonlinear diffusion of PDE can be expanded to:

\[
\frac{\partial}{\partial t} [f_t(x, y)] = \frac{\partial}{\partial x} \left[ c(x, y) \frac{\partial}{\partial x} f_t(x, y) \right] + \frac{\partial}{\partial y} \left[ c(x, y) \frac{\partial}{\partial y} f_t(x, y) \right] \tag{2.4}
\]

Substituting the time-derivative of \( f_t(x, y) \) by its forward difference and discretizing:

\[
\frac{f_{t+\Delta t}(x,y) - f_t(x,y)}{\Delta t} = \frac{\partial}{\partial x} \left[ c(x, y) \frac{\partial}{\partial x} f_t(x, y) \right] + \frac{\partial}{\partial y} \left[ c(x, y) \frac{\partial}{\partial y} f_t(x, y) \right] \tag{2.5}
\]

Let \( \Delta t = 1 \) and replacing \( c(x, y) \), as defined above with \(1 - p(x, y)\), it obtains:

\[
f_{t+1}(x, y) = f_t(x, y) + \frac{\partial^2}{\partial x^2} f_t(x, y) + \frac{\partial^2}{\partial y^2} f_t(x, y) - \frac{\partial}{\partial x} \left[ p(x, y) \frac{\partial}{\partial x} f_t(x, y) \right] - \frac{\partial}{\partial y} \left[ p(x, y) \frac{\partial}{\partial y} f_t(x, y) \right] \tag{2.6}
\]

Usually, \( f_t(x, y) \) is initialized by \( f_0(x, y) = f(x, y) \), where \( f(x, y) \) is the original noisy image. From the given mathematical derivatives, Matlab coding is implemented. The solution to the above equation yields a denoised image after a certain number of iterations.
2.5.2 Wavelet Transform Technique

One of the most basic problems in signal processing is to discover a suitable representation of the data that will facilitate an analysis process. One way to achieve this aim is by decomposition of the signal on a set of fundamental functions prior to processing in the transform domain (Bao & Zhang, 2003). Transform theory has played a key role in image processing for a number of years; it continues to be a topic of interest in theoretical as well as applied work in this field. Image transforms are used widely in many image processing fields, including image enhancement, restoration, encoding, and description.

2.5.2.1 Discrete Wavelet Transform Algorithm (DWT)

Overviews of the fast implementation of the discrete wavelet transform (DWT) as given by a literature review. The forward wavelet transform (FDWT) operation (termed also as decomposition or analysis) is given by the following equation:

\[
A_j(x, y) = f(x, y) \otimes H(y) \otimes H(x)
\]
\[
W_j^H(x, y) = f(x, y) \otimes H(y) \otimes G(x)
\]
\[
W_j^V(x, y) = f(x, y) \otimes G(y) \otimes H(x)
\]
\[
W_j^D(x, y) = f(x, y) \otimes G(y) \otimes G(x)
\]

(2.7)

where \(f(x, y)\) is the given image, \(\otimes\) denotes the convolution operation, and \(H\) and \(G\) are one dimensional low pass and high pass decomposition filters, respectively. The image is decomposed into four sub-bands; \(A_j\) denotes the low frequency approximation sub-band, \(W_j^i, i \in \{H, V, D\}\) denotes the high frequency sub-band at scale \(j\), and \(i\) being one of the horizontal (H), vertical (V), or diagonal (D) orientations. The original image can be reconstructed through the inverse wavelet transform (IDWT) operation (termed also as reconstruction or synthesis):

\[
f(x, y) = A_j(x, y) \otimes \tilde{H}(x) \otimes \tilde{H}(y) + W_j^H(x, y) \otimes \tilde{H}(y) \otimes \tilde{G}(x) +
W_j^V(x, y) \otimes \tilde{H}(x) \otimes \tilde{G}(y) + W_j^D(x, y) \otimes \tilde{G}(y) \otimes \tilde{G}(x)
\]

(2.8)
where $H$ and $\tilde{G}$ are one dimension allow pass and high pass reconstruction filters derived as conjugate or dual of the decomposition filters $H$ and $G$, which depend on whether the filters are orthogonal or bi-orthogonal, respectively. Assuming that the original image $f(x, y)$ is part of the scale-space such that the wavelet coefficients can be manipulated after decomposition, the original image and the reconstructed image can be considered as $f_t(x, y), f_{t+1}(x, y)$, respectively. Using this convention, writing the analysis and synthesis operations in joint form will give us the following formulation:

$$f_{t+1}(x, y) = $$

\[ [f_t(x, y) \otimes H H(x, y)] \otimes \tilde{H} H(x, y) + [f_t(x, y) \otimes G H(x, y)] \otimes \tilde{G} H(x, y) + \]

\[ [f_t(x, y) \otimes H G(x, y)] \otimes \tilde{H} G(x, y) + [f_t(x, y) \otimes G G(x, y)] \otimes \tilde{G} G(x, y) \]  \hspace{1cm} (2.9)

where $f(x, y) \otimes G H(x, y)$ is the separable convolution of $f(x, y)$ with $G(x)$ and $H(x)$ (Yang et al., 2010).

Transforming the above equation into Fourier domain produces the following mathematical expressions:

$$\hat{f}_{t+1}(w_x, w_y) = $$

\[ [\hat{f}_t(w_x, w_y) \cdot \hat{H} H(w_x, w_y)] \cdot \hat{H} H(w_x, w_y) + \]

\[ [\hat{f}_t(w_x, w_y) \cdot \hat{G} H(w_x, w_y)] \cdot \hat{G} H(w_x, w_y) + \]

\[ [\hat{f}_t(w_x, w_y) \cdot \hat{H} G(w_x, w_y)] \cdot \hat{H} G(w_x, w_y) + \]

\[ [\hat{f}_t(w_x, w_y) \cdot \hat{G} G(w_x, w_y)] \cdot \hat{G} G(w_x, w_y) \]  \hspace{1cm} (2.10)

$$\hat{f}_{t+1}(w_x, w_y) = $$

\[ \hat{f}_t(w_x, w_y) \cdot ([\hat{H} H(w_x, w_y) \cdot \hat{H} H(w_x, w_y)] + [\hat{G} H(w_x, w_y) \cdot \hat{G} H(w_x, w_y)] + \]

\[ [\hat{H} G(w_x, w_y) \cdot \hat{H} G(w_x, w_y)] + [\hat{G} G(w_x, w_y) \cdot \hat{G} G(w_x, w_y)] \]  \hspace{1cm} (2.11)

It is obvious from that the perfect reconstruction $f_{t+1}(x, y) = f_t(x, y)$ is guaranteed through inverse wavelet transform if,
\[ HH \cdot HH + GH \cdot GH + HG \cdot HG + GG \cdot GG = 1 \] (2.12)

This is the case of conventionally used orthogonal and bi-orthogonal wavelet transforms.

### 2.6 Image Quality Assessment Methods

Measurement of image quality is crucial in many image processing systems. Due to inherent physical limitations and economic reasons, the quality of images, audios, and videos could visibly degrade right from the point when they are captured to the point when they are viewed by a human observer. Finding the image quality measures that have high sensitivity to these distortions would help systematic design of coding communication and imaging systems and improving or optimizing the image quality for a desired quality of service at a minimum cost.

Measurement of image quality is very important to numerous image processing applications. Human being is highly visual creatures, which mean it can recognize each other from appearance. The main function of the human eye is to extract structural information from the viewing field, and the human visual system (HVS) is highly adapted for this purpose. Therefore, for the applications, in which images are ultimately to be viewed by human beings, the only accurate method of quantifying visual image quality is through subjective evaluation or assessment. However, subjective evaluation is usually too inconvenient because it is time-consuming and expensive. As a result, a lot of efforts have been made to develop objective image quality metrics that correlate with perceived quality (Abdul Rehman & Wang, 2012).

The goal of image quality assessment research is to design a method to measure the strength of the perceptual similarity between the test and the reference images. Many approaches have been taken in account by researchers to measure the quality of an image or for the assessment of images.

The first approach is called the error sensitivity approach. The test images data is considered as the sum of the reference image and an error signal, where it is assumed that the loss of perceptual quality is directly related to the visibility of the error signal. Most of HVS-based image quality assessment models attempt to weigh and combine different aspect of the error signal according to their respective visual
sensitivities, which are usually determined by psychophysical measurement. The short coming from this approach is that larger visible differences may not necessarily imply lower perceptual quality.

In the second approach, the observation process efficiently extracts and makes the use of information represented in the natural scene, whose statistical properties are believed to play a fundamental role in the development of the HVS. A clear example of the second approach is the structural similarity based image quality assessment method. This method is based on observation that natural images are highly structured, meaning that the signal samples have strong dependencies among themselves. These dependencies carry important information about the structure of the objects in the visual scene (Brunet et al., 2011).

The most commonly used objective image quality measures are; Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Metric (SSIM).

### 2.6.1 Signal-to-Noise Ratio (SNR)

Signal-to-noise ratio is also called as SNR or S/N; defined as the ratio of signal power to the noise power corrupting the signal. The Signal-to-Noise Ratio (SNR) is a defining factor when it comes to quality of measurement. A high SNR guarantees clear acquisitions with low distortions and artifacts caused by noise. The better your SNR, the better the signal stands out, the better the quality of your signals, and the better your ability to get the results you desire. SNR measurement is commonly used in the field of science and engineering fields. A ratio higher than 1:1 indicates more signal than noise. While SNR is commonly quoted for electrical signals, it can be applied to any form of signal (Naomi, 2009). The SNR is given by the following formula:

\[
(SNR)_{dB} = \frac{\text{var}(\text{avg}(I_{\text{denoised}}))}{\text{var}(\text{avg}(I_{\text{original}}))}
\]  

(2.13)
2.6.2 Mean Square Error (MSE)

This metric is frequently used in signal processing. The goal of a signal fidelity measure is to compare two signals by providing a quantitative score that describes the degree of similarity and the level of error or distortion between them. Typically, it is assumed that one of the signals is a pristine original, while the other is distorted or contaminated by errors as some noise (Baluja et al., 2013). The MSE is defined as follows:

\[
MSE = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} \left( I_{original}(i,j) - I_{denoised}(i,j) \right)^2 \tag{2.14}
\]

where

\( N, M \): give the size of the image.

\( I_{original}(i,j) \): is the pixel values at location \((i, j)\) of the original image before the denoising process.

\( I_{denoised}(i,j) \): is the pixel values at location \((i, j)\) of the image after denoising algorithm.

2.6.3 Peak Signal to Noise Ratio (PSNR)

PSNR stands for the peak signal-to-noise ratio. It is an engineering term used to calculate 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 (Goyal & Sekhon, 2011). The PSNR computes as:

\[
PSNR = 20 \log_{10} \frac{255}{RMSE} \tag{2.15}
\]

where RMSE denotes the root mean square error estimated between the original image and the denoised image.
2.6.4 Structural Similarity Index Metric (SSIM)

The structural similarity index (SSIM) method is a recently proposed approach to image quality assessment. It is widely believed that the statistical properties of the natural visual environment play a fundamental role in the evolution, development, and adaptation of the human visual system (HVS). An important observation about natural image signal samples is that they are highly structured. Structuring signal means that the signal sample exhibit strong dependencies amongst themselves, especially when they are spatially proximate. These dependencies carry important information about the structure of the objects in the visual scene. The principal hypothesis of structural similarity based image quality assessment is that the human visual system is highly adapted to extract structured information in the visual field, and therefore, a measurement of structure similarity or distortion should provide a good approximation to perceived image quality. The SSIM index is a method to measure the similarity or the differences between two sets of images. SSIM index is a full reference metric, in other words, the measure event of image quality is based on an initial uncompressed or distortion free image as reference (Napoleon & Praneesh, 2013). The SSIM is computes as:

\[
SSIM(x, y) = \frac{(2\bar{x}\bar{y} + C_1)(2\sigma_{xy} + C_2)}{(\sigma_x^2 + \sigma_y^2 + C_2)(\bar{x}^2 + \bar{y}^2 + C_1)}
\]  
(2.16)

where

\[ \bar{x}: \text{is the average of } x. \]

\[ \bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i \]  
(2.17)

\[ \bar{y}: \text{is the average of } y. \]

\[ \bar{y} = \frac{1}{N} \sum_{i=1}^{N} y_i \]  
(2.18)

\[ \sigma_x^2: \text{is variance of } x. \]
\[ \sigma_x^2 = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})^2 \]  
\[ (2.19) \]

\[ \sigma_y^2 \] is variance of y.

\[ \sigma_y^2 = \frac{1}{N-1} \sum_{i=1}^{N} (y_i - \bar{y})^2 \]  
\[ (2.20) \]

\[ \sigma_{xy} \] represents the standard deviation of x and y.

\[ \sigma_{xy} = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x}) (y_i - \bar{y}) \]  
\[ (2.21) \]

\[ C_1 = (k_1 L)^2, \quad C_2 = (k_2 L)^2; \] two variables to stabilize the division with weak denominator, L represents the dynamic range of the pixel values, and \( k_1 = 0.01 \) and \( k_2 = 0.03 \) by default (Napoleon & Praneesh, 2013).

2.7 Previous Related Work

2.7.1 Medical Image Denoising Methods

Liao et al. (2010) proposed image denoising technique based on bilateral filter. Bilateral filter (BF) is a famous filter in preserving details while smoothing the image and increases its luminance and contrast. However, its performance in image denoising is unsatisfied because the bilateral filter uses gray levels of pixels directly, which causes the propagation of noise. In context bilateral filter (CBF), the range of filter is not defined on the gray levels directly but it is defined in the context; therefore, it can be suppressed greatly.

Palhano (2010) presented a method for real-time denoising of ultrasound images. A developed version of the Non-Local-means method is presented that incorporates an ultrasound dedicated noise model as well as a graphic processor unit (GPU) implementation of the algorithm. The work was based on average and the results demonstrated that the proposed method is very efficient in terms of denoising quality and is real-time.

Manjón et al. (2010) proposed a denoising algorithm based on non-local mean. With this new method, information regarding the local image noise level is
used to adjust the amount of denoising strength of the filter. The information is obtained automatically from the images by using new local noise estimation. Proposed new noise-adaptive method was demonstrated to outperform the standard filter when spatially varying noise is present in the images.

Ruikar & Doye (2011) proposed wavelet based image denoising methods. Wavelet algorithms are useful tool for signal processing such as image compression and denoising. However, this technique is computationally faster and gives better results. Results based on different noise such as Gaussian, Poisson’s, salt and pepper, and Speckle was performed in this paper by using used signal-to-noise ratio as a measure of the quality of denoising. Some aspects that were analyzed in this paper may be useful for other denoising schemes, objective criteria for evaluating noise suppression performance of different significance measures. Some function gives better edge perseverance, background information, and contrast stretching in spatial domain.

Satheesh & Prasad (2011) proposed a medical image denoising algorithm using contourlet transform. It used thresholding technique for the purpose of segmentation and enhancement. Image preprocessing was used for the purpose of removing white Gaussian noise and enhancement. The proposed algorithm maintains edges while removing the noise from the images. Numerical results show that the proposed algorithm can obtain a higher peak signal-to-noise ratio (PSNR) than wavelet based denoising algorithms using MR Images in the presence of AWGN.

Bhardwaj & Singh (2012) proposed a novel approach of medical image enhancement based on Wavelet transform. Wavelet transform based denoising techniques are of greater interest because of their performance over Fourier and other spatial domain techniques. First, a medical image was decomposed with Haar transform. Then again, high-frequency sub-images were decomposed. Secondly, noise in the frequency field was reduced by the soft-threshold method. Then, high frequency coefficients are enhanced by different weight values in different sub images. Then, the enhanced image was obtained through the inverse Haar transform. Lastly, the image’s contrast is adjusted by nonlinear contrast enhancement approaches. The PSNR value of enhanced images with the method proposed = 38.53. Results of experiments showed that the algorithm not only can enhance an image’s contrast, but also can preserve the original image’s edge property effectively.
Luo & Zhu (2012) proposed a technique based on a reconstruction-average mechanism. At first, different parts of the original complete spectrum are chosen from each of which a signal is reconstructed using a singularity function analysis model. Denoising achieved by averaging these reconstructed signals is by the fact that each of them is the sum of the same noise-free signal and an additive noise of varying magnitude. The experimental results on both simulated and real monochrome images show that the proposed denoising method allows efficient denoising while maintaining image quality and presents significant advantages over conventional denoising methods.

Rani et al. (2012) proposed an image denoising techniques as comparative study. In their paper, a comparison has been made in suitability methods of image denoising to remove noise using different techniques. Visual information transmitted in the form of image is naturally corrupted by Gaussian noise, which is a classical problem in image processing. Therefore, wavelet denoising technique is used because of the ability to capture the energy of a signal with few energy transform values. However, the wavelet transform has drawbacks in extracting the information from the edges, curves of the image. Wavelet transforms works well for the salt and pepper noise. To overcome this drawback of wavelet transform, the curvelet transform has been proposed. The curvelet transform best suited for extracting the information at the edges and curves of an image. The curvelet transform works well to extract features of an image and has been proven to be the best for denoising of an image, but for the salt and pepper noise, the curvelet transform does not work well. Hence, comparison of the image denoising performance is shown in terms of PSNR and visual performance. The result showed that curvelet transform gave a better PSNR and visual performance than wavelet transform and other methods.

Tran et al. (2012) proposed a model which decomposes a 3D image into two components: the first one containing the geometrical structure of the image and the second one containing the noise. The algorithm of wavelet transform was used to filter out the noise from the image where several decomposition levels were used. The wavelet shrinkage property was used for enhancement purpose. The numerical implementation was described in the paper and some experiments for denoising a 3D MRI image were successfully performed.

Bhonsle et al. (2012) applied bilateral filtering on medical images, which are corrupted by additive white Gaussian noise with different values of variances. The
filter is a nonlinear and local technique that preserves the features while smoothing the images at the same time. It removes the additive white Gaussian noise effectively but its performance is poor in removing salt and pepper noise.

Ke Lu et al. (2012) investigate an adaptive denoising scheme based on the patch Nonlocal- means (NL-means) algorithm for medical imaging denoising. Compared with the traditional NL-means algorithm, the proposed adaptive NL-means denoising scheme has three unique features. It restricted local neighborhood, where the true intensity of each noisy pixel is estimated from a set of selected neighboring pixels to perform the denoising process. It calculates the weights to the similarity between the patch to denoise and the other patches candidates. It applies the steering kernel to preserve the details of the images. The proposed method has been compared with similar state-of-art methods over synthetic and real clinical medical images showing an improved performance in all cases analyzed.

Tsiotsios & Petrou (2012) proposed on the choice of the parameters for anisotropic diffusion (AD) in image processing. AD filtering is highly dependent on some crucial parameters such as conductance function, gradient threshold parameter, and stopping time of the iterative process. Various alternative options at each stage of the algorithm are examined and evaluated and the best choice is selected. The scheme is evaluated with the help of real and simulated images and compared with other state of the art schemes using objective criteria. They carefully studied all steps of the anisotropic diffusion algorithm and came up with the best choice among the various options at each step, describing a complete image- adapted denoising tool. Despite a stopping criterion, the level of the removed noise and the quality of the preserved edges are also considered. The scheme was evaluated using several images with different levels of noise. The most difficult images to improve with AD are those with many details and texture. This is not surprising as highly textured image shave significant levels of energy in the high frequencies too, where noise is supposed to dominate. It is expected that any noise suppression scheme will have difficulty with such images.

In Mredhula & Dorairangaswamy (2013), an extensive review on denoising of medical images was presented together with the classification of medical images into either Radiographic or Ultrasound or MRI or CT image. In addition, a brief description of the digital images and medical images as well as concise note on Radiography, Ultrasound, MRI and CT images were also presented.
2.7.2 Image Quality Assessment Methods

Sampat et al. (2009) introduced a new measure of image similarity called the complex wavelet structural similarity (CW-SSIM) index, and showed its applicability as a general purpose for image similarity index. The idea behind CW-SSIM is that certain image distortions lead to consistent phase changes in the local wavelet coefficients and that a consistent phase shift of the coefficients does not change the structural content of the image. Four case studies were conducted and they demonstrated the superiority of the CW-SSIM index against other indices such as Dice which commonly used for assessing the similarity of a given pair of images. Furthermore, it shows that the CW-SSIM index has a number of advantages compared to others. It is robust to small rotations and translations as property of wavelets. It provides useful comparisons even without a preprocessing image registration step, which is essential for other indices and it is computationally less expensive.

Abdul Rehman & Wang (2010) showed that the structural similarity (SSIM) index as a good perceptual image quality predictor. However, in many real world applications, such as network visual communications, SSIM is not applicable because its computation requires full access to the original image. This paper proposed a reduced-reference approach that estimates SSIM with only partial information about the original image. It extracts statistical features from a multi-scale and multi-orientation divisive normalization transforms and develops a distortion measure by following the philosophy analogous to that in the construction of SSIM method. An interesting linear relationship between reduced-reference SSIM estimate and full-reference SSIM was seen when the image distortion type is fixed not varied. A regression-by discretization method is then applied to normalize the measure between image distortion types. Live database was used to test the proposed distortion measure where it shows strong correlations with both SSIM and subjective evaluations. It also demonstrates how the reduced-reference features employed to partially repair a distorted image.

In Wang & Li (2011), perceptual image quality assessment algorithms share common two-stage structures which are local quality or distortion measurement followed by pooling. Significant progress has been made in measuring local image quality. Pooling stage is often done in an ad-hoc ways followed by lacking
theoretical principles and reliable computational models. When viewing natural images, the optimal perceptual weights for pooling should be proportional to the local information content that can be estimated in units of bit using advanced statistical models of natural images. Extensive studies based upon six publicly-available subject-rated image databases concluded with three useful findings as follows:

(i) Information content weighting leads to consistent improvement in the performance of image quality assessment algorithms.

(ii) Surprisingly, with information content weighting even the widely criticized peak signal-to-noise-ratio can be converted to a competitive perceptual quality measure when compared with state-of-the-art algorithms.

(iii) The best overall performance is achieved by combining information content weighting with multi-scale structural similarity measures.

Brunet et al. (2011) proposed a class of metrics for signals and images deriving mathematically was considered as elements of reduce noise based upon the SSIM index. The important feature of this construction is that it considers the two terms of the SSIM index, which are normally multiplied together to produce a scalar as components of an ordered pair. However, each of these terms is then used to produce a normalized metric, in which one operates by the means of the signals while the other operates on their zero-mean components. This algorithm shows that a suitable norm of an ordered pair of metrics defines a metric in the RN.

2.8 Summary of the Chapter

Image enhancement is a process of improving the visual quality of an input image, which is more suitable for the human observer. Digital images can be enhanced by improving the perceptibility or improving the structural features. The main purpose of image enhancement is to bring out detail that is hidden in an image or to increase contrast in a low contrast image. Whenever an image is converted from one form to another such as digitizing the image, some form of degradation occurs at the output. Image enhancement is among the simplest and most appealing areas of digital image processing. The varieties of enhancement techniques are available for digital images. Appropriate choices of such techniques are greatly influenced by the image modality,
REFERENCES


