UNIVERSITI TEKNOLOGI MALAYSIA

UNIVERSITI PENYELIDIKAN

Enhancement of Mammogram Image Based on Two Stage Denoising Filtering and Contrst Limited Adaptive HistogramEqualization

By

Chasib Hasan Abboodi

Supervisor

Prof.Dr. Dzulkifli Mohamed

ABSTRACT

Digital mammography proved its efficacy in the diagnosis of breast cancer as an adequate and easy tool in detection tumors in their early stages. Mammograms have useful information on cancer symptoms such as micro calcifications and masses, which are difficult to identify because mammograms images suffer from some defects such as high noise, low-contrast, blur and fuzzy. In addition, mammography has major problem due to high breast density that obscures the mammographic image leading to more difficulty in differentiating between normal dense tissue and cancerous tissue. Therefore, for accurate identification and early diagnosis of breast cancer, mammograms images must be enhanced. Image enhancement commonly focuses on enhancing image details and removing noises. Using image-processing techniques for mammogram images helps to differentiate a special data that contain specific features of the tumors, which could be helpful in classifying benign and malignant tumors. This research focuses on salt and pepper noise removing and image enhancement to increase the mammography quality and improve early breast cancer detection. To achieve this purpose, a special technique is used that includes two stages image denoising base filtering and one stage for contrast enhancement. The filtering stages include the using of median and wiener filters. The contrast enhancement stage uses contrast limited adaptive histogram equalization (CLAHE). The evaluation of the performance is measured by PSNF and MSE for the filters and by contrast histogram for the CLAHE. The results show better performance of the research technique compared with other methods in terms of high PSNR(47.4750) and low MSE(1.1645) For future work, the technique will be evaluated with other type of noise.

CHAPTER 1

INTRODUCTION

1. OVERVIEW

Researchers around the world are making continuous efforts for early detection of breast cancer as a successful way to identify the disease and eliminate its effects. Radiographic examination is one of the means of early detection of this disease. By this mean, images for the breast are taking by x-ray, which is able to detect small changes and delicate tissue that may indicate the presence of a malignant disease. The computer has helped greatly in supporting and developing means of screening and diagnosing this disease.

1.1 Breast Cancer

Breast cancer is one of the most dangerous types of cancer among women all over the world. It happens to over 11% women during their lifetime. The World Health Organization named International Agency for Research on Cancer (IARC) estimates that more than one million cases of breast cancer will occur worldwide annually and more than 400,000 women die each year from this disease. Early detection of breast cancer is essential in reducing life fatalities.

However, achieving this early detection of cancer is not an easy task. Although the most accurate detection method in the medical environment is biopsy, it is an aggressive invasive procedure that involves some risks, patient discomfort and high cost (Eltoukhy *et al*, 2009).

1.2 Detect Breast Cancer

There are many techniques for detect breast lesions, like ultrasonography and magnetic resonance imaging. But mammography has proven to be the most effective tool for detecting breast cancer in its earliest and most treatable stage, so it continues to be the primary imaging modality for breast cancer screening and diagnosis (Dos Santos Teixeira 2012; Urbana Ivy et al., 2012).

A mammogram is an x-ray exam of the breast that's used to detect and evaluate breast changes. X-rays were first used to examine breast tissue nearly a century ago, but modern mammography has only existed since the late 1960s, when special x-ray machines were designed and used just for breast imaging. Since then, the technology has advanced a lot, and today's mammogram is very different even from those of the 1980s and 1990s (American cancer society).

Mammography has major problems due to high breast density which obscures the mammographic image. A woman's breasts are naturally denser, or more glandular when young, which makes it difficult for the radiologist to analyze the mammogram image. Technology to detect breast cancer is changing rapidly, with recent entrants to the field like digital mammography and computer aided detection. Enhancing the image by manipulation of fine differences in intensity by means of image processing algorithms forms the basis of any computer aided detection system (Eltoukhy et al., 2009).

1.3 Computer Aided Mammography

The mammograms interpretation is a visual task and is subject to human error. Computer-aided image interpretation has been proposed to help radiologists to perform this difficult task. Research into the use of computers to detect breast cancer in mammograms has been underway for many years. In the most common approach, a computer automatically analyses a digitized mammogram and attempts to locate signs of cancer. Detections are displayed to clinicians as prompts on a computer screen or paper printout (Rose, 2005).

Digital mammography has been used in attempts to reduce the negative biopsy ratio and the cost to society by improving feature analysis and refining criteria for recommendation for biopsy. Digital mammography is a convenient and easy tool in classifying tumors, and many applications in the literature proved its effectiveness in breast cancer diagnosis. Image features extraction is an important step in image processing. The features of digital images can be extracted directly from the spatial data or from a different space. Using a different space by a transform such as Fourier transform, wavelet transform or curvelet transform can be helpful to separate a special data. Detecting the features of image texture is a difficult process since these features are mostly variable and scale-dependent (Eltoukhy et al., 2009).

2. PROBLEM BACKGROUND

Quantum noise prevails in situations where an image is created by the accumulation of photons over a detector. Typical examples are found in standard x-ray films, CCD cameras, mammograms, and infrared photometers (Naseem et al., 2012).

X-ray mammography is the most common technique used by radiologists in the screening and diagnosis of breast cancer (Mencattini et al., 2008). But, the quality of the breast mammogram images may suffer from poor resolution or low contrast because of the limitations of the X-ray hardware systems in mammogram machines (Naseem et al., 2012). Although it is seen as the most reliable method for early detection of breast carcinomas, reducing mortality rates by up to 25%, its interpretation is very difficult where 10%–30% of breast lesions are missed during routine screening (Mencattini et al., 2008).

X-ray mammography suffers from many problems. The main predominant and more likely problem to occur in mammogram images is quantum noise due to electrical fluctuation (Naveed et al., 2011). Quantum noise occurs in the mammogram images during acquisition due to low count X-ray photons. It affects the quality of images. It also affects the classification accuracy to classify images into benign and malignant (Naseem et al., 2012).

Also, Mammography has major problem due to high breast density that obscures the mammographic image leading to increase the differentiating difficulty between normal dense tissue and cancerous tissue when looking for small tumors surrounded by glandular tissues. To increase the diagnostic performance of radiologists, several computer-aided diagnosis schemes have been developed to improve the detection of either of the two primary signatures of this disease named masses and micro-calcifications.

Mass enhancement introduces much more difficult problems with respect to micro-calcifications. In fact, because of low contrast, they appear embedded in and camouflaged by varying densities of parenchymal tissue structures. Thus, it is very difficult to visually detect them on mammograms (Mencattini et al., 2008).

Radiologists mainly estimate breast density by visual judgment of the imaged breast. Thus automatic tissue classification methods try to imitate such visual judgment, learning from the radiologist experience. In the literature different approaches for classifying breast tissue based only on the use of histogram information have been proposed (Zhou et al., 2001). Radiographic density is a scheme or measure aiming to explain or find a correlation between density and cancer risk, but the technique lacked objectivity due to intra and inter observer variations.

Recently, researchers have used many techniques to analyze radiographic density in digital images, and used many techniques to classify breast density pattern. When mammograms are analyzed by computer, the pectoral muscle should preferably be excluded from processing intended for the breast tissue. In the literature different approaches for automatic pectoral muscle segmentation have been proposed. Segmentation of the breast and the pectoral muscle are often prerequisites for automatic assessment of breast density (Kwok et al., 2004).

However, in many of the approaches used, the entire breast including the pectoral muscle has been proposed to extract features. The inclusion of the pectoral muscle can affect the results of intensity based image processing methods in the detection of breast densities (Velayutham and Thangavel, 2012).

3. PROBLEM STATEMENT

Mammography has major problems due to high breast density, which obscures the mammographic image. The main drawback of mammography today is that it is hard to differentiate between normal, dense tissue and cancerous tissue when looking for small tumors surrounded by glandular tissues. The accurate mammography depends on the degree of image clarity and lack of noise. All the image processing techniques used for enhancing mammography contrast and noise removal achieved the ambition of researchers but did not achieve optimal results. The research aims to use image processing techniques to improve the image quality by removing the noise and improving the image contrast (Naseem et al., 2012).

4. RESEARCH AIM

This research investigates the use of image processing techniques for enhancing mammographic images quality in order to help radiologists in taking the right decision in the process of early diagnosis of breast cancer.

5. OBJECTIVES

The main objective of this research is to enhance the breast cancer detection as a variation from normal appearance by:

1. Using two stages image denoising base median and wiener filters to remove the noise in mammogram images

2. Applying contrast limited adaptive histogram equalization (CLAHE) to enhance the mammogram images

6. RESEARCH SIGNIFICANCE

Breast cancer recently is the most popular cancer among women worldwide. Mammography has been the most dependable and efficient screening measure for breast cancer early detection. Mammography suffers from a big problem, which is the difficulty of differentiating between tumor tissue and normal ones in high efficiency that leads sometimes to an error in the diagnostic process and often causes of cancer death among women worldwide. This research aims to remove the noise that increases the image blurry, and enhances its quality to consolidate the cancer diagnostic process.

7. H SCOPE RESEARC

This research focuses on noise removing and image enhancement to increase the mammography quality to improve early breast cancer detection. Two stage of filtering include median and wiener filters will be used for noise removal because they can perform better than single techniques. Contrast Limited Adaptive Histogram Equalization (CLAHE) will be used to enhance the image contrast.

The Mammographic Institute Society Analysis (MIAS) database will be used in this research according to the various cases it includes (Eltoukhy et al., 2009).

8. RESEARCH OUTLINE

This research will be organized in five chapters as follows. Chapter 1 shows the introduction. Chapter 2 reviews the literature. The research methodology is explained in chapter 3, which covers the research procedure, data and proposed technique. Chapter 4 illustrates the results and discussion, while the conclusions and recommendations are in chapter 5.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

Cancer can affect all age's even human embryos, but the risk of infection increases with age progress. The cancer can cause death in a large proportion more than all other death causes. The common cancer types are Lung cancer, breast cancer, ovary cancer, colon cancer and liver cancer. Breast cancer is one of the most dangerous types of cancer among women all over the world (Urbana Ivy et al., 2012), and one of the major causes of mortality increase to middle-aged women, especially in developed countries. Therefore, early detection becomes the key to improving the breast cancer prognosis and reducing the mortality rates (Zhang et al., 2013). Currently, it is well known that mammography is the most effective method for early detection of breast cancer (Ponraj et al., 2011). However, it is very difficult to interpret the X-ray mammograms because of the small differences in image density of various breast tissues, in particular, for dense breasts (Kim et al., 1997).

A suspicious mammographic finding may lead to perform a breast biopsy. About 75% of certain mammograms fall into indeterminate grades of radiological suspicion. One would like to avoid recommending unnecessary biopsy because of the costs and discomfort to the patient. Moreover, biopsy can confound later mammographic testing by producing radiographic abnormalities which can be mistaken for cancer (Bandyopadhyay, 2011).

2.2 METHODS OF DIAGNOSIS BREAST CANCER

Detecting cancer in its initial stages helps to contain the disease, in addition to avoid its deadly symptoms and prevent its spread. Different types of lesions can indicate breast cancer, such as micro-calcifications, masses and architectural distortions, but some other diseases have patterns similar to the breast cancer, which makes the diagnosis difficult (Dos Santos Teixeira 2012). There are many testing options to detect breast cancer such as mammography, Magnetic Resonance Imaging (MRI), Ultrasound, X-ray, biopsy, etc. (Urbana Ivy et al., 2012). Biopsy is the most accurate method in the medical environment but it is an aggressive invasive procedure that includes some risks, patient discomfort and high cost (Eltoukhy et al., 2009).

2.2.1 Effectiveness of Mammography

Mammography is a particular form of radiography, using radiation levels between specific intervals with a purpose to acquire breast images to diagnose an eventual presence of structures that indicates a disease, especially cancer (Dos Santos Teixeira, 2012). Mammogram is the most effective and easy tool to detect it early (Urbana Ivy et al., 2012) (Mencattini et al., 2008) (Ponraj et al., 2011) in spite of their problems (Naseem et al., 2012) (Mencattini et al., 2008) (Naveed et al., 2011) such as:

- Poor resolution or low contrast
- Quantum noise due to electrical fluctuation

- Difficulty to interpret mammogram images
- Difficulty to differentiate between normal dense tissue and cancerous tissue and quantum noise due to high breast density which obscures the mammographic image

Mammography is highly accurate, but like most medical tests, it is not perfect. On average, mammography will detect about 80–90% of the breast cancers in women without symptoms (Ponraj et al., 2011).

A possible sign of breast cancer is the appearance of clustered micro calcifications whose individual particles are usually under 0.5 mm in diameter with irregular and heterogeneous shape. Detection of individual micro calcifications is difficult because their shape and size are variable and they may be embedded in dense tissues areas. Thus, accurate diagnosis should be performed for the clustered micro calcifications that may indicate an early stage cancer (Kim et al., 1997).

Researchers have attempted different image enhancement methods for digitized mammograms to enhance the visibility of mammographic lesions. Image enhancement is commonly performed by emphasizing image details and removing noises.

Recently, researchers have studied intensity-histogram features and applied threshold techniques and fractal characteristics to analyze radiographic density in digital images. Subashini et al. (2010) classified breast tissue based on the intensity level of histogram of a mammogram using SVM. Statistical features of a mammogram are extracted using simple image processing techniques. This technique uses texture models to capture the mammographic appearance within the breast.’

Byng et al. (1996) proposed measures were based on skewness and fractal dimension. Texture-based discrimination between fatty and dense breast types applying granulometric techniques and Laws texture masks has been investigated in. Spatial gray level dependency matrices were constructed and features estimated based on these matrices to classify breast tissue.

Urbana Ivy et al. (2012) used wavelet and curve let transform to diagnose breast cancer in digital mammogram taken from Mini-Mias database. They used Multi resolution analysis based on 2-level discrete wavelet transform to detect micro calcification clusters to assist radiologists in breast cancer diagnosis. The image multi resolution analysis reduces noise and views the image in different components.

2.3 MAMMOGRAPHY IMAGE QUALITY

Mammograms have useful information on cancer symptoms such as micro calcifications and masses, which are highly complicated to identify because mammograms images suffer from some defects such as high noise, low-contrast, blur and fuzzy. Therefore, for accurate identification and early diagnosis of breast cancer, mammograms images must be enhanced (Sangeetha and Saradha, 2013). The image quality can be identified through measuring contrast noise ratio, signal noise ratio, modulation transfer function, noise, the uniformity and various artifacts (Chevalier et al., 2012).

2.3.1 Modulation Transfer Function (MTF)

The MTF is a quantitative and objective measurement of the image quality that can be provided by a system. MTF gives information about the magnitude of the object contrast, which is transferred to the image as a function of the spatial frequency (Chevalier et al., 2012).

Dos Santos Romualdo et al. (2009) enhanced image by using a restoration inverse filter, calculated based on the image system modulation transfer function (MTF). This pre-processing technique was used for a set of mammographic phantom images measure the number of microcalcifications correctly detected by a computer-aided detection (CAD) algorithm.

2.3.2 Noise

Noise is any undesired information that disfigures an image. It is a random difference of brightness or color information in images produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is commonly considered as an undesirable by image capture product. Noise appears in digital image during image acquisition process, which converts an optical image into a continuous electrical signal that is then sampled.

There are many ways in which, noise can be introduced into an image, based on how the image is created. Mammography images contain noise signals leading to distort the image and increase the difficulty to understand and study it. Hence, it needs the use of proper filters to limit or reduce the noise to increase the possibility of better interpretation of the content of the image (Al-amri et al., 2010; Patidar et al., 2010).

2.3.2.1 Types of Noise

There are three common types of image noise namely Impulsive Noise, Salt & Pepper Noise and Speckle Noise (Al-amri et al., 2010; Patidar et al., 2010), but some researchers add Poisson noise as a forth type (Maheswari and Radha, 2010):

1. Random Variation Impulsive Noise (RVIN)

This noise is a major part of the "read noise" of an image sensor, that is, of the constant noise level in dark areas of the image.

This type of noise is also called the Gaussian noise or amplifier noise or normal noise is randomly occurs as white intensity values. Gaussian distribution noise can be expressed by:

$P(x) = 1/(\sigma\sqrt{2\pi}) * e^{(x-\mu)2} / 2\sigma^{2 -\infty < 0 < \infty}$ *(1)*

Where: *P(x)* is the Gaussian distribution noise in image; μ and σ is the mean and standard deviation respectively.

2. Salt & Pepper Noise (SPN)

This type contains random occurrences of both black and white intensity values, and often caused by threshold of noise image.

Salt & pepper distribution noise can be expressed by:

p(x) = (2) $\left\{ ==otherwiseBxpAxp,0,2,1 \right.$

Where: *p1*, *p2* are the Probabilities Density Function (PDF), *p(x)* is distribution salt and pepper noise in image and *A, B* are the arrays size image. Gaussian and salt & Pepper are called impulsive noise. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by dead pixels, analog-to-digital converter errors, bit errors in transmission, etc. Salt & Pepper noise is one of the most popular noises in an image. It is also called fixed-valued impulse noise.

3. Speckle Noise (SPKN)

If the multiplicative noise is added in the image, speckle noise is a ubiquitous artifact that limits the interpretation of optical coherence of remote sensing image. The distribution noise can be expressed by:

$J = I + n*I$ (3)

Where, J is the distribution speckle noise image, I is the input image and n is the uniform noise image by mean o and variance v (Al-amri et al., 2010).

Speckle degrades the quality of images and thereby reducing the ability of a human observer to discriminate the fine details of diagnostic examination. Images with speckle noise will results in reducing the contrast of image and difficult to perform image processing operations like edge detection, segmentation (Prakash et al., 2011).

4. Poisson noise

Poisson noise or shot noise is an electronic noise type that occurs when a limited number of particles that carry energy such as electrons in an electronic circuit are small enough to increase statistical fluctuations in a measurement (Patidar et al., 2010). Figure 2.1 shows all noise types.

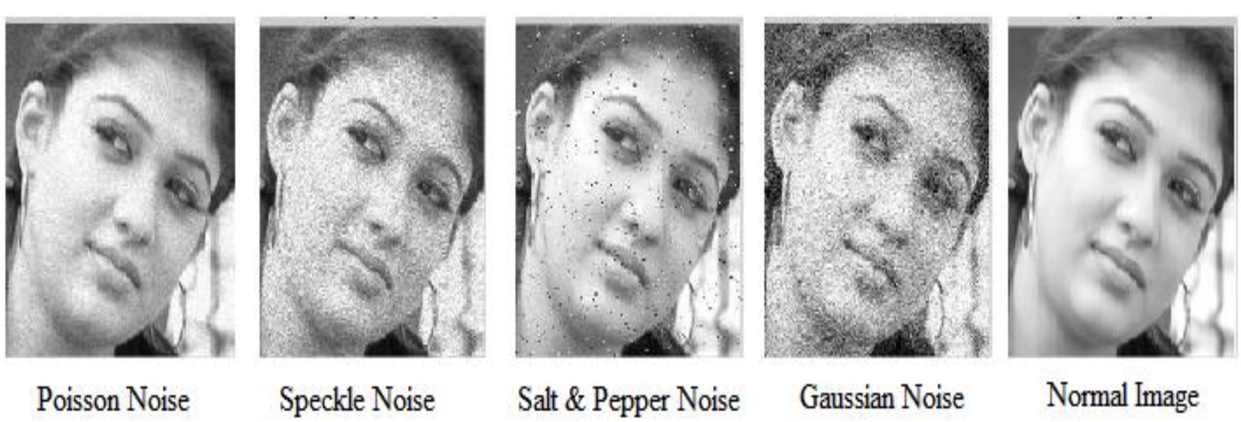


Figure 2.1: Noise Types (Patidar et al., 2010)

2.3.3 Uniformity

The uniformity of gain is corrected by using flat-field to improve quality in digital imaging. The non-uniformity of the detector sensitivity is corrected through a gain map and is also used to correct all the images acquired. Furthermore, any single defective detector (pixel) can be replaced with a reasonable combination of adjacent detector signals (pixel). The non-uniformity can cause artifacts due to differences in the pixel-to-pixel sensitivity (Chevalier et al., 2012).

2.3.4 Artifacts

Artifacts are undesirable characteristics which are not related to the mammary anatomic structures of a radiographic image. They can affect the image clarity by hiding or simulate a lesion on detection. Artifacts can be caused by the source of X-rays, the beam filter, the compression device, breast support, grid, and flaws in processing, amongst others (Chevalier et al., 2012).

2.4 ENHANCING MAMMOGRAPHY IMAGES

The most crucial task in analysis of mammogram image is the image enhancement. The enhancement aims to enhance the contrast of details and features while suppressing the background significantly. Image enhancement modifies an image attributes to make it more convenient for a certain task and a specified observer.

Many techniques can enhance a digital image without making damage to it. The enhancement includes modifying the image brightness, contrast or the distribution of the grey levels. The enhancement methods can be divided into two categories (Maini and Aggarwal, 2010):

1. Spatial Domain Methods

2. Frequency Domain Methods

In spatial domain techniques, researchers directly deal with the image pixels, where they can manipulate the pixel values to achieve the required enhancement. In frequency domain methods, the image is first transferred in to frequency domain, which requires calculating the Fourier Transform of the image 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.
Image enhancement improves the quality (clarity) of images for human viewing. Removing blurring and noise, increasing contrast, and revealing details are examples of enhancement operations (Gopal, 2012; Patel et al., 2012).

The use of computers in processing and analyzing biomedical images allows more accurate diagnose by a radiologist. Humans are susceptible to committing errors and their analysis is usually subjective and qualitative. Objective and quantitative analysis facilitated by the application of computers to biomedical image analysis leads to a more accurate diagnostic decision by the physician (Bozek et al., 2008).

Computer aided detection or diagnosis (CAD) is an important application of image aiming at assisting doctors in making right diagnostic decisions about detecting cancer and reducing the probability of failure. The most computer-aided detection and diagnosis computational algorithms in mammographic image analysis consist of typical steps, but image enhancement is usually needed (Dos Santos Teixeira 2012). Current CAD systems rely heavily on sophisticated techniques in machine learning to address the area of image processing, pattern recognition and classification (Gopal, 2012).

Kim et al. (1997) proposed an adaptive enhancement method for mammographic image, which is based on the first derivative and the local statistics. Image local statistics are used for adaptive enhancement realization, which leads to enhance image details and suppress its noises. The method yields good results comparing with the conventional image enhancement methods for a simulated image with respect to contrast improvement ratio (CIR), which was utilized by the researchers as an objective performance measure.

2.5 DIGITAL IMAGE PROCESSING

Digital image processing is the most important technique used in remote sensing. It has helped in the access to technical data in digital and multi-wavelength, services of computers in terms of speed of processing the data and the possibilities of big storage (Al-amri et al., 2010).

Image processing is basically the use of computer algorithms to perform image processing on digital images. Digital image processing is a part of digital signal processing. Digital image processing has many significant advantages over analog image processing because it is fast, flexible, and precise. Image processing allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing of images (Patidar et al., 2010). Image pre-processing techniques are necessary, in order to find the orientation of the mammogram, to remove the noise and to enhance the quality of the image (Ponraj et al., 2011). Image processing researchers have developed various images enhancement algorithms. Most image processing algorithms include typical steps illustrated in Figure 2.2.

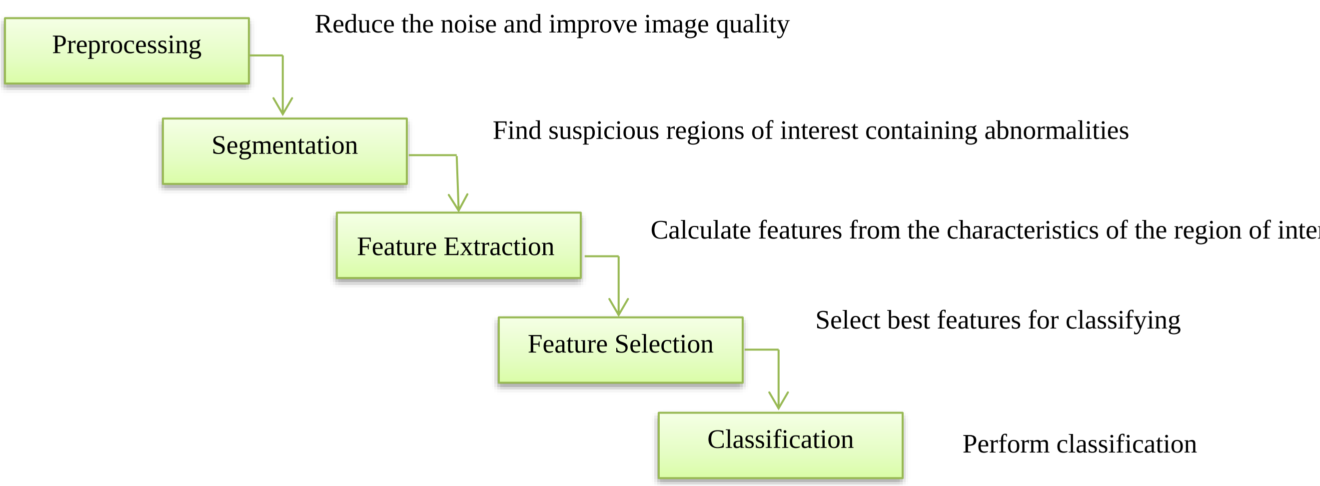


Figure 2.2: Typical Steps in Image Processing Algorithms

2.5.1 Image Contrast Enhancement

Several researches have been done in contrast enhancement field, which can be divided into two main areas of research. The first is global contrast enhancement techniques such as histogram equalization, fuzzy logic enhancement, homomorphic filtering, etc. the second is Local contrast enhancement techniques. Global contrast enhancement techniques are easy and robust but cannot adjust to the local brightness features of the input image because these techniques use only global information gathered over the whole image (Christian, 2011). Local contrast enhancement methods are more convenient in digital mammography field because of the uniformity of the image (Bozek et al., 2009).

One of the most important objectives of mammogram image enhancement is to enhance the contrast between regions of interest and the background (Sangeetha & Saradha, 2012). Image enhancement is converting the image to a form easy to analyze by a human or machine processes using different techniques that aim to enhance the image visual appearance (Vij & Singh, 2009).

Currently, contrast stretching, histogram equalization spatial domain filtering, frequency domain filtering (Homomorphic filtering), Wavelet Transform (WT), mathematical morphology etc. are the major commonly used image preprocessing techniques. Although those techniques have achieved good enhancement results to some extent, however, it is still far from being satisfactory (Sangeetha & Saradha, 2012). However, most contrast enhancement algorithms enhance the image and noise simultaneously (Shen, 2013).

Morrow et al. (1992) introduced region based contrast enhancement technique by identifying the region for feature of interest through the seed growing technique use. Then, the contrast between the region of interest and its background was enhanced to create more separation between their intensity levels, which made the interest region more visible to the observer. Veldkamp and Karssemeije (2000) used local contrast enhancement with adaptive noise equalization, which was more effective than using a fixed noised equalization alone. Cheng et al. (2002) used the fuzzy logic in contrast enhancement to enhance selected feature such as microcalcifications (MCC) while maintaining the noise amplification to a minimum.

Subr et al. (2005) described the average local contrast of an image by a scalar objective function. They represented the contrast enhancement problem as an optimization problem that attempts to maximize the image average local contrast in a controlled fashion without saturation of colors. Their enhancement is done without image segmentation in frequency or spatial domains. They used an efficient greedy algorithm controlled by a single input parameter to solve this optimization. Their technique performs well comparing with other existing global and local contrast enhancement techniques.

2.5.1.1 Histogram

A histogram is the estimation of the probability distribution of a particular type of data. The image histogram represents the value recurrence of certain color in an image. An image histogram is a type of histogram, which offers a graphical representation of the tonal distribution of the gray values in a digital image. By viewing the image's histogram, we can analyze the frequency of appearance of the different gray levels contained in the image (Krutsch and Tenorio, 2011).

Histogram equalization (HE) is a method in image processing of contrast adjustment using the image histogram. IT generates a gray map, which changes the histogram of an image and redistributing all pixels values to be as close as possible to a user specified desired histogram. HE allows for areas of lower local contrast to gain a higher contrast. Histogram equalization automatically determines a transformation function seeking to produce an output image with a uniform Histogram (Vij & Singh, 2009).

However, in some type of images, histogram equalization can show noise hidden in the image after the processing is done. This is why it is often used with other imaging processing techniques (Krutsch and Tenorio, 2011).

HE does not preserve the average brightness of the input image in the output image. Therefore, the processed output image will often appear unnaturally bright. Also, HE may increase the contrast of background noise, while decreasing the usable signal. To overcome these drawbacks, numerous variations of the classic HE technique have been published (Christian, 2011; Shen, 2013).

Histogram Equalization is accomplished by linearizing the cumulative density function of the image intensity levels. Consider a discrete grayscale image and let ni be the number of occurrences of gray level i. A normalized histogram of the image shows the probability of occurrence of a pixel of level i in the image, and would be given by a collection of probability values for each pixel level (Christian, 2011):

P (xi) = probability that pixel x has gray level i = ni / n

where n = the total number of pixels in the image. The cumulative density function for this histogram would be given by:

$$cdf_x(i) = \sum_{j=0}^{i} p(x_i)$$

Yoon et al. (2009) introduced a new contrast enhancement technique using sub-histogram equalization based new contrast enhancement algorithm, which are preventing over-equalization and acquiring global contrast enhanced effect. The algorithm divides the original histogram into sub-histograms with reference to brightness level. The sub-histograms are enhanced by sub-histogram equalization. The enhanced sub-images are merged to construct the final image. The algorithm improves feature which has low density and broadly distributed without distortion.

To enhance the HE performance and improve images contrast, Contrast Limited Adaptive Histogram Equalization (CLAHE) is used. On the contrary of ordinary histogram, the adaptive histogram constructs several histograms; each one represents an image section, and uses them to redistribute the image illumination values. Adaptive histogram equalization is capable to improve an image's local contrast, provide more detail in the image**.** But, it also can produce noise.

Talha et al. (2011) used CLAHE to enhance the mammography image quality. Vij & Singh (2009) used different enhancement techniques of histogram such as Histogram Equalization (HE), Brightness Preserving Bi- Histogram Equalization (BBHE) and Adaptive Histogram Equalization (CLAHE). The BBHE gives better results in terms of lowest mean square error MSE and highest peak signal to noise ratio PSNR.

2.5.1.2 Homomorphic Filtering

Homomorphic filtering is a frequency domain method for contrast enhancement. It has been used in a variety of applications like shadow identification, underwater image pre-preprocessing, contrast enhancement for raised or indented characters, and seismic data processing. Homomorphic filtering sharpens features in an image by enhancing high frequencies and sharpening object edges. It also flattens lighting variations in an image, bringing details out of shadows. It provides simultaneous dynamic range compression (reducing illumination variation) and contrast enhancement (increasing reflectance variation). Homomorphic filtering can thus prove to be most effective on images that have large variations in lighting (Christian, 2011).

2.5.1.3 Wavelet Transform

Wavelet Transformation (WT) is a mathematical tool for analyzing signals and images in time frequency domain. It decomposes signals or images into different functions called wavelet family in which all of the basic functions are derived from scaling and translation of single function called the mother wavelet. Representing signals or images in time frequency domain has two main advantages: (a) an optimal resolution both in the time and frequency domains; and (b) lack of stationary nature of the signal (Rajkumar & Raju, 2011). There are two main types of wavelet transform continuous and discrete. Because of computers discrete nature, computer programs use the discrete wavelet transform. The discrete transform is very efficient from the computational point of view (Ruikar and Doye, 2011).

Wavelets provide a very sparse and efficient representation for images, but it can't efficiently represent discontinuities along edges or curves in images or objects (Eltoukhy et al., 2009). The drawback of wavelet transform is the method in which problem of filling missing data will occur and the PSNR value is very low (Sangeetha & Saradha, 2012). It is first necessary to denoise the data before using the wavelet because the presence of noise could disturb the processing in the wavelet domain and could frustrate the enhancement operation (Mencattini et al., 2008)

In image enhancement methods based on wavelet, the image is decomposed into various subbands. After the decomposition, modification of wavelet coefficients at various subbands is done to denoise the signal or enhance the contrast. The enhanced image is reconstructed from the modified wavelet coefficients (Shen, 2013).

Laine et.al (1995) first used wavelet in mammogram contrast enhancement. They applied a three level dyadic wavelet to decompose the mammographic images and a functional mapping to enhance the contrast and remove the noise simultaneously. Fig 2.3 shows the general scheme. DWT is the discrete wavelet transform and IDWT is the inverse discrete wavelet transform, x (n) and y (n) are original signal and processed signal, respectively. The original signal is decomposed by the DWT and then processed by thresholding scheme or nonlinear function mapping and reconstructed with the IDWT to produce the denoised or enhanced signal/image.

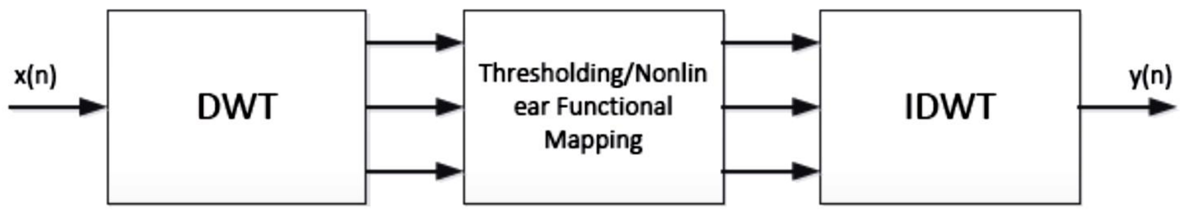


Figure 2.3: Wavelet based scheme (Laine et al., 1995)

Kumar et al. (2012) used modified mathematical morphology and biorthogonal wavelet transform to enhance digital mammographic images contrast and remove the noise. Wavelet transform includes three operations: wavelet decomposition, thresholding detail coefficients and wavelet reconstruction. Approximation and detail coefficients are obtained by decomposition. For the detail coefficients level dependent threshold is applied. Finally the decomposed image is reconstructed by the approximation and the modified detail coefficients. The results show that this method provides better image quality comparing to other contemporary methods

Rajkumar and Raju (2011) used discrete wavelet transformation (DWT) and stationary wavelet transformation (SWT) to classify mammogram images into normal, benign and malignant. In each wavelet transformations, a partial part of the highest wavelet coefficients is used as features for classification. The DWT provided better classification in case of benign and malignant images, but the stationary wavelet transformation performed better in classifying normal images.

Sangeetha and Saradha (2013) proposed curvelet transform to enhance mammogram image. The curvelet transform is a recent extension of ridgelet transform that overcome ridgelet weaknesses in medical image segmentation. Curvelet transform is an expansion of wavelet and ridgelet transforms, which aims to deal with exciting fact occurring along curves. It is found from the experiments that proposed image enhancement method using curvelet transform is efficient and useful in capturing relevant clinical information.

2.5.2 Noise Removal

Image denoising is a digital image processing procedure aiming to remove noise, which may corrupt an image during its acquisition or transmission, and retain its quality. Noise removal is fundamental in medical imaging applications in order to enhance and recover useful details that may be hidden in the data (Satheesh and prasad, 2011). Noise removal is one of the significant preprocess to enhance mammography images. Several techniques are used effectively to remove various types of noise in digital images**.**

Typically, the noisy signal is defined as a noise-free signal with added noise signal (Shen, 2013):

$$y(n) = x(n)+h(n)$$

where y(n) is the noisy signal, x(n) is the noise-free signal and h(n) is the pure noise signal. In order to recover the noise-free signal from the noisy signal, signal denoising will be applied to remove or reduce the additive noise.

2.5.2.1 Independent Component Analysis (ICA)

In this method, a set of multidimensional data vectors are represented in a way to make the components independent as far as possible. This means that a transformation should be found to provide a vector whose components are sparse. ICA denoising methods are based on the fact that the transformed components have sparse distributions (super Gaussian), thus, these methods try to reduce Gaussian noise by these sparse components shrinkage. The shrinkage function choice relies on each sparse component statistical distribution. Mayo et al. (2004) made a comparison among different denoising techniques namely Wiener filter, Wavelet and ICA. The results were quantitative measured by using the squared root of the mean squared error (RMSE) between the denoised image and the original noise free image. The denoising results for the three techniques are comparable from the MSE and visual point of view.

2.5.2.2 Wavelet Denoising

In denoising, there is always a trade-off between noise suppression and preserving actual image discontinuities. To remove noise without excessive smoothing of important details, a denoising algorithm needs to be spatially adaptive. The wavelet representation, due to its sparsity, edge detection and multiresolution properties, naturally facilitates such spatially adaptive noise filtering. A common procedure is: (1) Compute the discrete wavelet transform (DWT); (2) Remove noise from the wavelet coefficients and (3) Reconstruct the denoised image. The scaling coefficients are usually kept unchanged, unless in certain cases of signal dependent noise (Pizurica, 2002).

Wavelet denoising procedure can be given as follows (Rangarajan et al., 2002). Assume that the observed data is

$$X(t) = S(t) + N(t)$$

where S (t) is the uncorrupted signal with additive noise N (t). Let W (.) and W^{-1} (.) denote the forward and inverse wavelet transform operators. Let D (., λ) denote the denoising operator with threshold λ. We intend to denoise X (t) to recover $\hat{S}(t)$ as an estimate of S (t). The procedure can be summarized in three steps

$$Y = W(X)$$

$$Z = D(Y, \lambda)$$

$$\hat{S} = W^{-1}(Z)$$

D (., λ) being the thresholding operator and λ being the threshold.

In wavelet domain each noisy coefficient is modified according to certain threshold calculated. The threshold is applied to each noisy coefficient to obtain better performance (Kumar et al., 2012). Small coefficients are dominated by noise, while coefficients with a large absolute value carry more signal information than noise. Replacing noisy coefficients (small coefficients below a certain threshold value) by zero and an inverse wavelet transform may lead to a reconstruction with less noise. The thresholding idea based on the following assumptions (Rangarajan et al., 2002):

- The decorrelating property of a wavelet transform creates a sparse signal: most untouched coefficients are zero or close to zero.

- Noise is spread out equally along al coefficients.

- The noise level is not too high so that the signal wavelet coefficients can be distinguished from the noisy ones.

It is clear that thresholding is a simple and efficient method for noise reduction. Moreover, inserting zeros creates more sparsity in the wavelet domain. Threshold determination is an important question when denoising. A small threshold may yield a result close to the input, but the result may still be noisy. A large threshold on the other hand, produces a signal with a large number of zero coefficients, which leads to a smooth signal. More smoothness may destroy details and cause blur and artifacts (Rangarajan et al., 2002).

Ruikar and Doye (2011) used Wavelet to remove noise while preserving original information of the image. They presented new threshold function that performs well in preserving the contrast, edges, background of the images.

Rangarajan et al. (2002) investigated wavelet thresholding in denoising noisy signals. They tested hard and soft on noisy versions of the standard 1-D signals and found the best threshold. Then, they compared many soft thresholding schemes namely VisuShrink, SureShrink and BayesShrink with universal thresholding for denoising images. The result showed that these thresholding techniques perform better than the universal thresholding, especially BayesShrink.

Mencattini et al. (2008) proposed a novel algorithm for image denoising and enhancement based on dyadic wavelet processing. The denoising stage is based on the limited iterative noise difference evaluation. In addition, in the case of micro calcifications, the author proposed an adaptive change of improvement degree at various wavelet scales, while in the case of mass discovery; it developed an original segmentation technique combining dyadic wavelet information with mathematical morphology. The new approach consists of using the similar method core for giving out images to distinguish both micro calcifications and masses. The proposed system have been experienced on a great number of scientific images, comparing the consequences with those obtained by some other algorithms projected in the literature through both logical indexes and the suggestions of radiologists. During introduction tests, the method seems to considerably recover the diagnosis in the premature breast cancer discovery with respect to other approaches.

2.5.2.3 Filters

The success of restoring an image is affected by some image properties under corruption process, such as the complexity of the image scene and the parameters and properties of the filter (Arastehfar, 2013). Image filtering is not only used to improve image quality but also is used as a preprocessing stage in many applications including image encoding, pattern recognition, image compression, and target tracking.

Filters are classified into linear filters and non-linear filters. Linear filters blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal-dependent noise. Non-linear filters remove the noise without any attempts to explicitly identify it (Maheswari and Radha, 2010).

Many filtering techniques have been used to restore images; each one has its own features, advantages and defects.

1. Mean Filter (MF)

Mean Filter (MF) is a simple linear filter, 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 neighbors, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Mean filtering is based around a kernel, which represents the shape and size of the neighborhood to be sampled when calculating the mean (Al-amri et al., 2010). The mean filter is used to reduce Gaussian noise (Hargaš et al., 2003; Al-amri et al., 2010).

2. Standard Median Filter (SMF)

Median filter is the non-linear filter which changes the image intensity mean value if the spatial noise distribution in the image is not symmetrical within the window, which leads to reduce the variance of the intensities in the image. Median filter is a spatial filtering operation, so it uses a 2-D mask that is applied to each pixel in the input image. The noise is removed by replacing the window center value by the median value of center neighborhood. Standard median filtering (SMF) is a non-linear, low-pass filtering method which can be used to remove 'speckle' noise from an image. A median filter can outperform linear, low pass filters, on this type of noisy image became it can potentially remove all the noise without affecting the 'clean' pixels. Traditional median filter is used to reduce salt-pepper noise (Al-amri et al., 2010). Median filter (MF) is widely used in impulse noise removal methods due to its denoising capability and computational efficiency (Hosseini, & Marvasti, 2011).

Median filter now is broadly used in reducing noise and smoothing the images (Ilango and Marudhachalam, 2011). Maheswari and Radha (2010) indicated that median filter is one of the most popular nonlinear filters for removing Salt & Pepper noise. The noise is removed by replacing the window center value by the median value of center neighborhood.

The median filter is popular because of its demonstrated ability to reduce random impulsive noise without blurring edges as much as a comparable linear low pass filter (Ilango and Marudhachalam, 2011).

3. Adaptive Wiener Filter (AWF)

Wiener filter is the classical denoising filter, which is a linear filter that minimizes the mean squared error (MSE). The adaptive Wiener filter is a local low pass filter that is processed adaptively in a local neighborhood of 3x3 pixels blocks of an image, estimating the local image mean and standard deviation of each of them. The adaptive filter is better than a similar linear filter, where it preserves edges and other image high frequency parts (Mayo, et al., 2004).

Adaptive Wiener Filter (AWF) changes its behavior based on the statistical characteristics of the image inside the filter window. Adaptive filter performance is usually superior to non-adaptive counterparts. But the improved performance is at the cost of added filter complexity (Al-amri et al., 2010).

Naveed et al. (2011) used Wiener filter to handle the possible quantum noise, which is more likely to occur in mammograms. Dos Santos Romualdo et al. (2009) also used Wiener filter to reduce quantum noise.

Khireddine et al. (2007) used different filters for digital image restoration. The results showed that the wiener filter generates a lower error than other filters.

Kumar et al. (2011) tested the performance of wiener filter against different filters in removing white noise. The results showed that the wiener filter is more suitable for restoration than a variety of smoothing filters such as the Gaussian, median, mean filters.

4. Gaussian Filter (GF)

Gaussian low pass filter is an impulse responsive, which designed to give no overshoot to a step function input while minimizing rise and fall time. Gaussian is smoothing filter in the 2D convolution operation that is used to remove noise and reduce blur from image (Al-amri et al., 2010).

5. Adaptive Median Filter (AMF)

The adaptive median filter (AMF) is designed to eliminate the problems faced with the standard median filter. The basic difference between the two filters is the variation of window size surrounding each pixel in the adaptive median filter. This variation depends on the median of the pixels in the present window. If the median value is an impulse, then the size of the window is expanded (Al-amri et al., 2010).

Patidar et al. (2010) used Mean filter, Median filter and Wiener filter to remove all types of noise from an image. The results showed that the Wiener Filter is better in removing Speckle, Poisson and Gaussian noise, while Median filter is better in removing Salt & Pepper noise.

Maheswari and Radha (2010) used median filter to remove salt & pepper noise from various types of compound images. The performance of the median filter is compared and analyzed according to Peak Signal to Noise Ratio (PSNR) value and gives better results for compound document images in comparison with scanned compound images.

Shinde et al. (2012) used various filtering to remove the speckle noise from medical images. The results showed that the median filter performs better for the noisy image in terms of standard derivations and mean.

6. Max and Min filter

The max filter is useful for finding the brightest points in an image. Also, because pepper noise has very low values, it is reduced by this filter as a result of the max selection process in the sub image Sxy. Max filter is given by

$$\hat{f}(x, y) = \max_{(s, t) \in S_{xy}} \{g(s, t)\}$$

The min filter is useful for finding the darkest points in an image. The min filter is given by

$$\hat{f}(x, y) = \min_{(s, t) \in S_{xy}} \{g(s, t)\}$$

7. Fuzzy Filters

Fuzzy techniques have been applied in image processing different domains such as filtering, interpolation, and morphology. Several fuzzy filters have been developed for noise reduction, such as the well-known FIRE-filter, the weighted fuzzy mean filter, and the iterative fuzzy control based filter. Most fuzzy techniques for image noise reduction mainly deal with fat tailed noise like impulse noise. These fuzzy filters are able to surpass order filters such as the median filter. In general, most fuzzy techniques are not specifically designed to deal with Gaussian noise or give satisfactory results when used to handle such noise (Mahesh et al., 2010).

Van De Ville et al. (2003) introduced a new fuzzy filter to reduce images additive noise. The filter includes two stages; the first one calculates a fuzzy derivative for eight different directions. The second stage uses these fuzzy derivatives to perform fuzzy smoothing by weighting the contributions of neighboring pixel values. Both stages are based on fuzzy rules, which make use of membership functions. The filter can be applied iteratively to effectively reduce heavy noise.

Krishnan and Viswanathan (2013) proposed new fuzzy image filter for images noise reduction contaminated with Gaussian noise by using fuzzy rules, which make use of membership functions. Fuzzy derivative concept is also applied to perform fuzzy smoothing. This method provides better input for further image processing techniques and also it increases the contrast of the images.

Kaur and Gupta (2012) proposed a fuzzy logic based adaptive noise filter to reduce salt & pepper noise. It has the ability to preserve fine image details, edges and textures. The filter detects firstly the intensity of the salt & pepper noise. If a noise pixel is detected, it will be subjected to the next filtering stage. If a pixel has no noise, it will be kept and the filtering action is spared to prevent altering any fine image details and textures included in the original image.

Kundra et al. (2011) proposed a filter based on fuzzy logic for impulse noise reduction and contrast enhancement. Fuzzy inference system (FIS) is used to take the decision about the pixels of the image under consideration. The work is done in two stages. In the first stage, the noise in the images is removed and in the second stage, contrast is improved. The output image generated is noise-free high-contrast image.

2.6 SUMMARY

This chapter addresses the importance of mammography quality in early detection of cancer and the methods used to improve the quality of mammographic images to enhance breast tumors classification to increase the diagnosis accuracy of the disease in its initial stages. Noise concept and types are explained, in addition to their effect on mammography images such as image distortion and increase the difficulty to understand and interpret it. The chapter also elucidates image processing techniques, especially the ways to improve image contrast, remove noise that hinder the diagnostic process, as well as explores the benefits and problems of these techniques.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 INTRODUCTION

Among various breast imaging techniques, mammography is remaining the effective diagnostic and screening tool to detect breast cancer at its initial stages. Researchers have attempted various image processing techniques to enhance the visibility of mammography. Image enhancement commonly focuses on enhancing image details and removing noises. This chapter explains the methodology of the research, which aims to enhance the mammographic image contrast and remove noise. The methodology includes research design and approach.

3.2 RESEARCH DESIGN

The research design describes the research procedure starting from reviewing the literature to study the current image processing techniques capable to solve the research problem resuming identifying the required techniques to enhance the mammography image contrast and remove the noise. In addition, the design includes a comparison between the research method and other techniques. The research design is shown in figure 3.1.

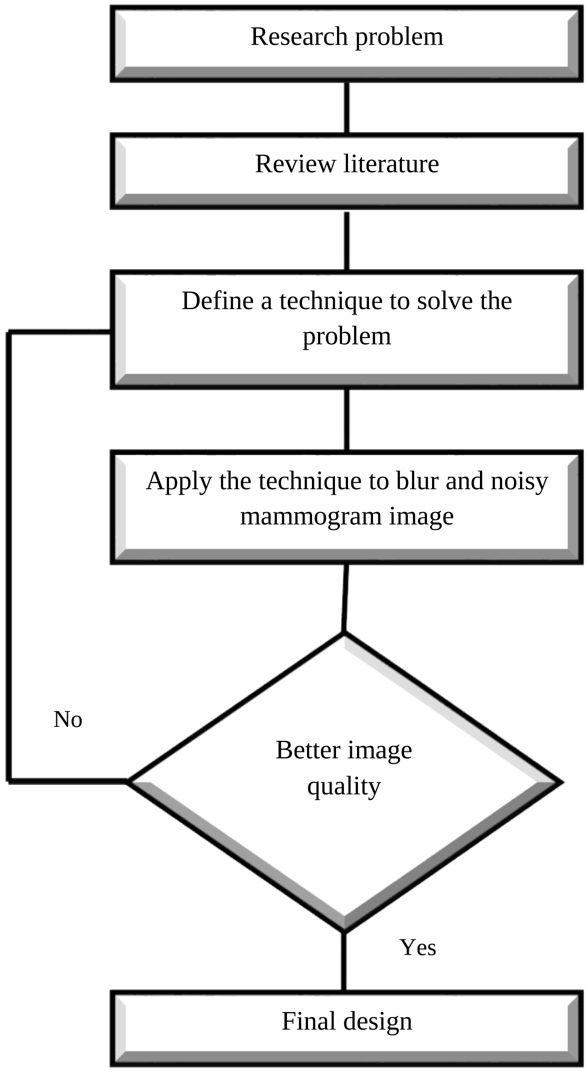


Figure 3.1: Research Framework

3.3 RESEARCH TECHNIQUE DESIGN

The research aims to enhance the mammogram image contrast and suppress the noise. For contrast enhancement, a generalization of adaptive histogram equalization called contrast limited adaptive histogram equalization (CLAHE). For removing noise, two stages image denoising base filtering are used. These two filtering stages are used to suppress noise in the images. Therefore, the noise in the first stage is removed. The remaining noise in form of random dark or light spots is tackled during contrast enhancement. In the second stage of filtering, any remaining noise from first stage in addition to the possible noise that may produce by the contrast enhancement is treated. The proposed design of the research technique is illustrated in figure 3.2 below.

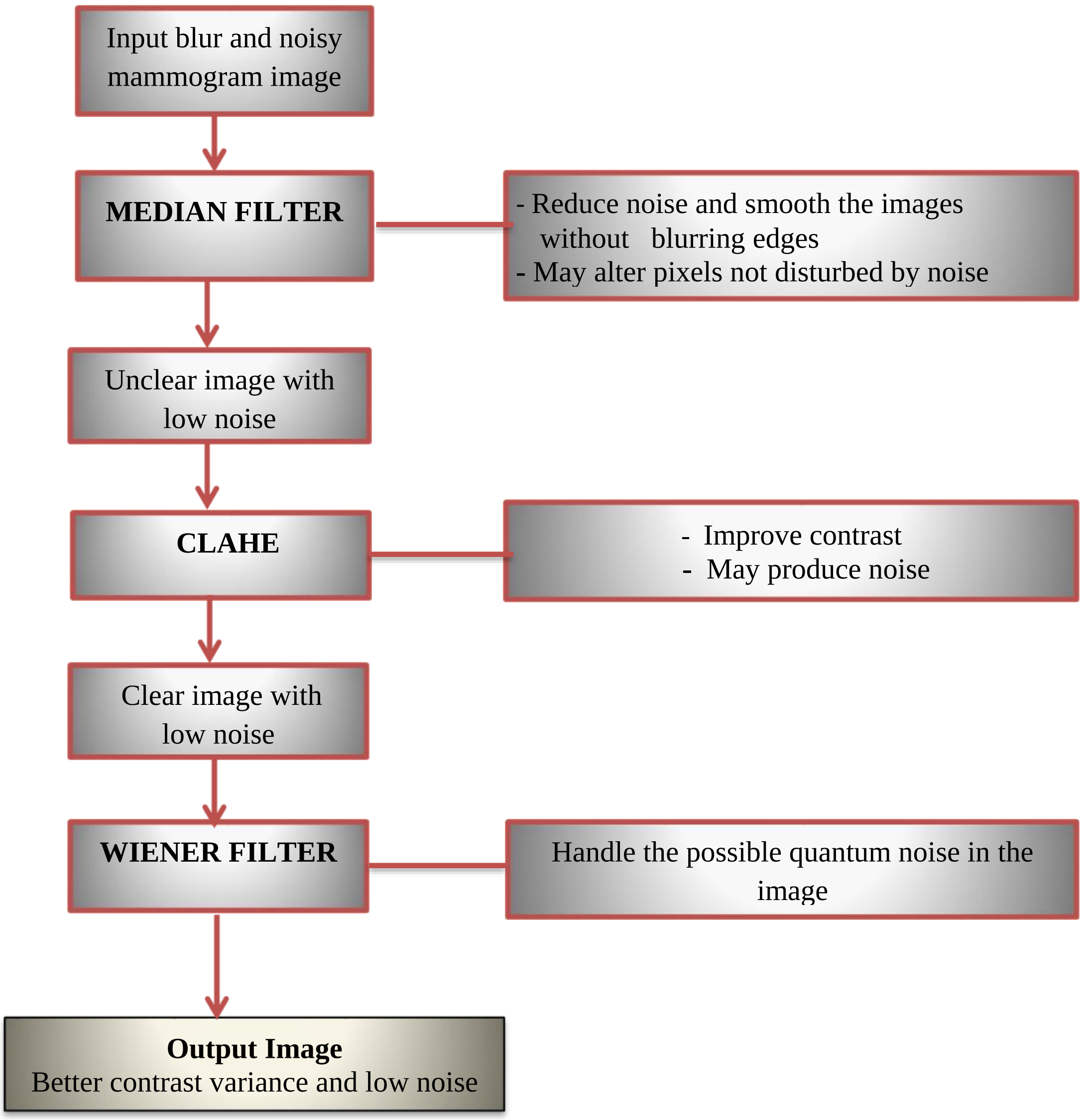


Figure 3.2: The Proposed Techniqu

3.3.1 Median Filter (MF)

Median filter is the non-linear spatial filter. It can be used to remove ‘speckle’ noise from an image and it outperforms linear, low pass filters, on this type of noise (Al-amri et al., 2010). Median filter is widely used in impulse noise removal methods due to its denoising capability and computational efficiency (Hosseini, & Marvasti, 2011). Median filter now is broadly used in reducing noise and smoothing the images without blurring edges (Ilango and Marudhachalam, 2011). Median filter is one of the most popular nonlinear filters for removing Salt & Pepper noise (Maheswari and Radha, 2010; Ramani et al., 2013). The several of median filter is I) Centre-weighted median filter II) weighted median filter III) Max-median filter, the effect of the size of the window increases in median filtering noise removed effectively (Ramani et al., 2013).

A median filter is based on moving a window over an image and computing the output pixel as the median value of the brightnesses within the input window. If the window is $J * K$ in size we can order the $J * K$ pixels in brightness value from smallest to largest. If $J * K$ is odd then the median will be the $J * K + 1/2$ entry in the list of ordered brightnesses (Khireddine et al., Pue2007).

One of the main disadvantages of the basic median filter is that it tends to alter the pixels not disturbed by noise (Ilango and Marudhachalam, 2011). However, it often fails to perform well in denoising additive Gaussian noise.

This filter is used firstly because it can reduce noise and smooth the images without blurring edges. In addition, it can perform well with different noises. If this filter modifies the pixels that did not disturbed by noise, we can handle it in the other stages.

3.3.2 Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE is a special case of the histogram equalization technique that works adaptively on the image that needs enhancement. The intensity of the pixel is transformed to a value within the display range proportional to the rank of pixel intensity in the local intensity histogram. CLAHE is an improvement of Adaptive Histogram Equalization (AHE) where the enhancement calculation is adjusted by imposing a user-defined maximum, i.e. clip level, to height of the local histogram and thus on the maximum contrast enhancement factor. The enhancement is done in highly uniformly areas of the image, which prevent high noise enhancement and decreases the edge-shadowing effect of unlimited AHE (Maitra et al., 2012).

Histogram equalization (HE) as an image processing method is used for adjusting contrast using the image histogram. HE produces noise and does not keep the average brightness of the input image, thus the processed output image will often appear unnaturally bright. Histogram equalization also may increase the contrast of background noise, while decreasing the usable signal. To enhance the HE performance and improve images contrast, Contrast Limited Adaptive Histogram Equalization (CLAHE) is used. This technique can handle the problem of noise amplification of histogram equalization.

The CLAHE operates on small regions in the image called tiles rather than the entire image. Each tile’s contrast is enhanced. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise and reduce edge-shadowing effect that might be present in the image (Maitra et al., 2012). Adaptive histogram equalization is capable to improve an image's local contrast, provide more detail in the image. However, it also can produce noise (Vij & Singh, 2009).

To overcome this problem, two stages image denoising base filtering is used. In the first stage, the median filter is used, and in the second stage, the wiener filter is used. The CLAHE can improve the local contrast of image and give more detail in the image, but it will increases the noise same as most control enhancement techniques. The noise increase will not reach unsatisfied level because the noise is already suppressed by the median filter in the first filtering stage.

3.3.3 Wiener Filter

The wiener filter seeks to build an optimal estimate of the original image by enforcing a minimum mean square error constraint between estimate and original image. The wiener filter is an optimum filter (Ramani et al., 2013).

The Wiener filter purpose is to reduce the amount of noise present in a signal by comparison with an estimation of the desired noiseless signal. Wiener filter is the classical denoising filter, which is a linear filter that minimizes the mean squared error (MSE). This filter is better than a similar linear filter because it can maintain edges and other image high frequency parts (Mayo, et al., 2004).

The error between the input signal f (m, n) and the estimated signal f (m, n) is given by (Ramani et al., 2013).

$$E(M, N) = F(M, N) - F(M, N) \quad (1)$$

The square error is given by

$$[F(M, N) - F(M, N)]^2 \quad (2)$$

The mean square error is given by

$$E\{[F(M, N)-F(M, N)]^2\}$$

The Wiener filter is also one of the good linear filtering methods, and is widely known for its good performance in denoising the white noise (Kumar et al., 2011). Wiener filter can handle the possible quantum noise in images (Naveed et al., 2011).

This filter is used in the second stage of filtering because it has the ability to minimize the mean squared error (MSE), which is an effective performance measure. It is expected that the output image will have better contrast variance and low noise.

3.4 RESEARCH DATA

The Mammography Image Analysis Society (MIAS) is an organization in UK. It is a research group interested in the mammogram images study. They have created a digital mammography database for research purpose (Rajkumar and Raju, 2011).

The MIAS data set is used in the research experiments. This data set includes various cases and vastly used in comparable research work. It contains 322 mammograms of right and left breast from 161 patients. These mammograms are distributed as 51 Malignant, 64 Benign and 207 Normal. Some of these images will be used in the research experiments (Eltoukhy et al., 2009; Naveed et al., 2011).

3.5 RESEARCH APPROACH

The research follows the experimental approach as follows.

- Black and white images from MIAS are subjected to salt and pepper. This kind of noise is selected because it randomly occurs in white and black image.

Removing and detecting this noise is a challenge and complex process because image data as well as the noise share the same small set of values 0 or 1(Maheswari and Radha, 2010).

- The research technique is applied to the images to test its efficiency in contrast enhancement and noise removing.
- The results of the research's technique will be compared with other stages in terms of peak signal to noise ratio (PSNR) and mean squared error (MSE).
- Mat lab (R2010) is used to conducts the research experiments. The Mat lab tool box for image processing, which supports a wide range of techniques, is used.

3.6 SUMMARY

This chapter explains the research methodology, which includes the design of the technique that is used to carry out the objectives of the research in addition to the research data and approach. The importance of the technique and the purpose of its use as a whole are explained, in addition to explain the objective of each of its components. The research approach, which includes the experiment procedure, is described.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

Digital mammography has many advantages over conventional film mammography such as shorter exams and faster image acquisition, easier image storage and transmission to other physicians. Moreover, the computer processing of breast images is more accurate in the detection of breast cancer (Bandyopadhyay, 2011).

The literature demonstrated the effectiveness of digital mammography in the diagnosis of breast cancer as an adequate and easy tool in detection tumors in their early stages. Using image-processing techniques for mammogram images helps to differentiate a special data that contain specific features of the tumors that could be helpful in classifying benign and malignant tumors (Eltoukhy et al., 2009). The main approach of this research is to enhance the mammogram images by removing noise and enhancing the images contrast.

4.2 The Proposed Technique

The research goal is to enhance the mammogram image contrast and suppress the noise by using a special technique as shown in figure 4.1, which includes two stages image denoising base filtering and one stage for contrast enhancement. The filtering stages include using median and wiener filters. The contrast enhancement stage uses contrast limited adaptive histogram equalization (CLAHE). The two filters are used to get rid of noise in the different stages.

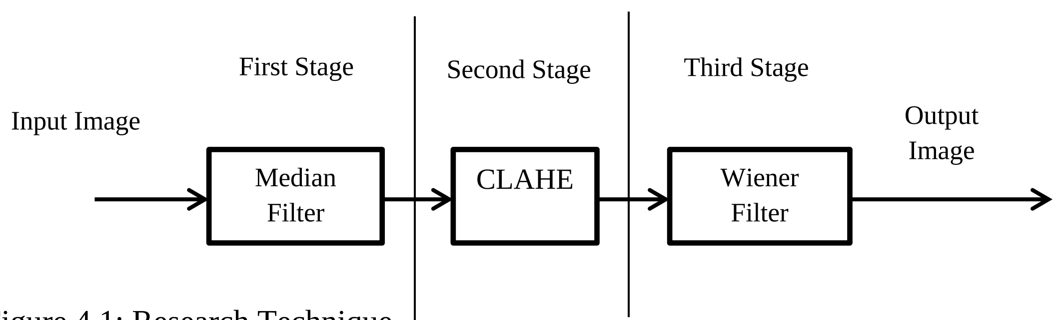


Figure 4.1: Research Technique

The filters attempt to remove Salt & Pepper noise, which is added in different densities to the MIAS images. The major challenge in removing such noise from binary image is due to the fact that image data as well as the noise share the same small set of values (either 0 or 1), which complicates the process of detecting and removing the noise (Maheswari and Radha, 2010).

4.3 Evaluation of Noise Reduction

The presence of noise affects the quality and clarity of the images and thus reduces the degree of tumor diagnosis. Removing noise from degraded images is a challenging research field in image processing. It involves estimation procedure of the image corrupted by noise. Several filtering techniques have been used for restoring image, each of which has its own pros and cons. Applying filters is based on the on the nature of the corruption process, and the properties of the filter (Arastehfar, 2013).

In order to evaluate the proposed technique for noise reduction, several images are selected from the database and different densities of salt and pepper noise are added to the images. The performance evaluation of the filtering operation is quantified by the PSNR (Peak Signal to Noise Ratio) and MSE (Mean Square Error). The higher the PSNR in the restored image, the better is its quality (Ramani et al., 2013).). The higher of MSE value refers to the lower image quality. The MSE and PSNR are calculated by the following equations (Al-amri et al., 2010; Vij & Singh, 2009):

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right)$$

Where,

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{i=1}^{N}[g(i,j) - f(i,j)]^2$$

Where, *M* and *N* are the total number of pixels in the horizontal and the vertical dimensions of image. *g* denotes the Noise image and *f* denotes the filtered image.

The CLAHE and the filters were implemented using (MATLAB R2010) and tested various noise densities. The tests have been done on three mammographic images taken from the Digital Database for Mammography MIAS.

4.4 Evaluation of Contras

Contrast enhancement techniques are used widely to improve the visual quality of images. The difference in luminance reflected from two adjacent surfaces creates contrast between the surfaces in the image. The greater the contrast, the easier it is to recognize and differentiate objects in an image. Thus, object contrast is an important factor in the perception of the visual quality of an image and in its usefulness for object recognition and image analysis applications (Christian, 2011).

The CLAHE is applied to the mammogram images. The contrast histogram is a graph of the distribution of contrast over the image. The enhanced image's contrast histogram should contain more regions at higher contrast levels than the original image's contrast histogram. A low-contrast image is the one with a narrow contrast histogram (Morrow et al., 1992). The performance evaluation in contrast process is evaluated by the histogram contrast.

4.5 Results

The results of each stage in terms of image quality are presented separately, and the results in terms of PSNR and MSE are presented in separate tables. The histogram contrast is illustrated and explained separately.

4.5.1 Images Qualities

The original images to the first stage are corrupted by different Salt &Pepper noise with various standard deviations 005, 0.1, and 0.15.

1. The Output image when the salt & pepper is 0.05 is shown in figure 4.

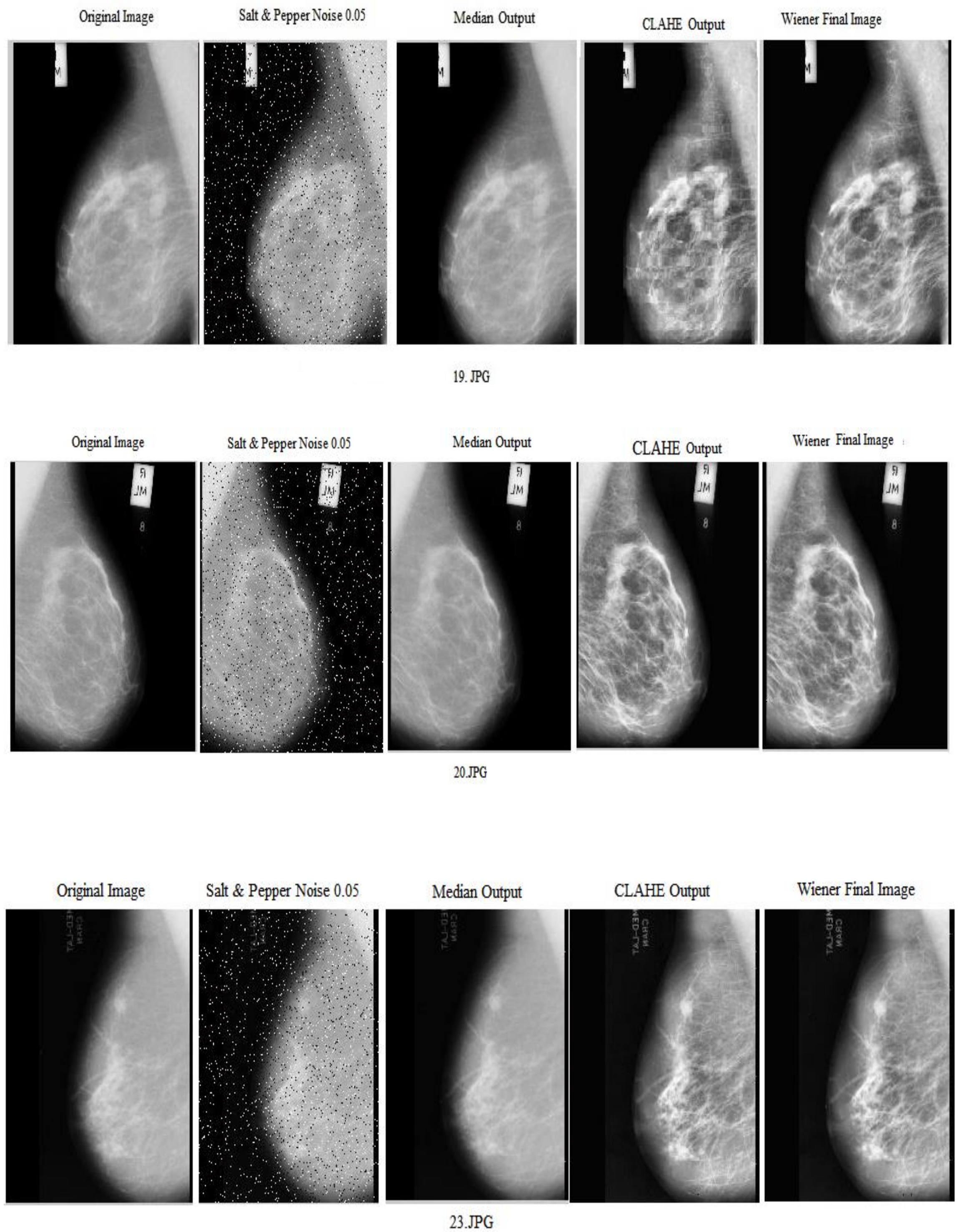


Figure 4.2: The Results When the Salt &Pepper is 0.05 db

2. The Output image when the salt &pepper is 0.15 is show in figure 4.3.

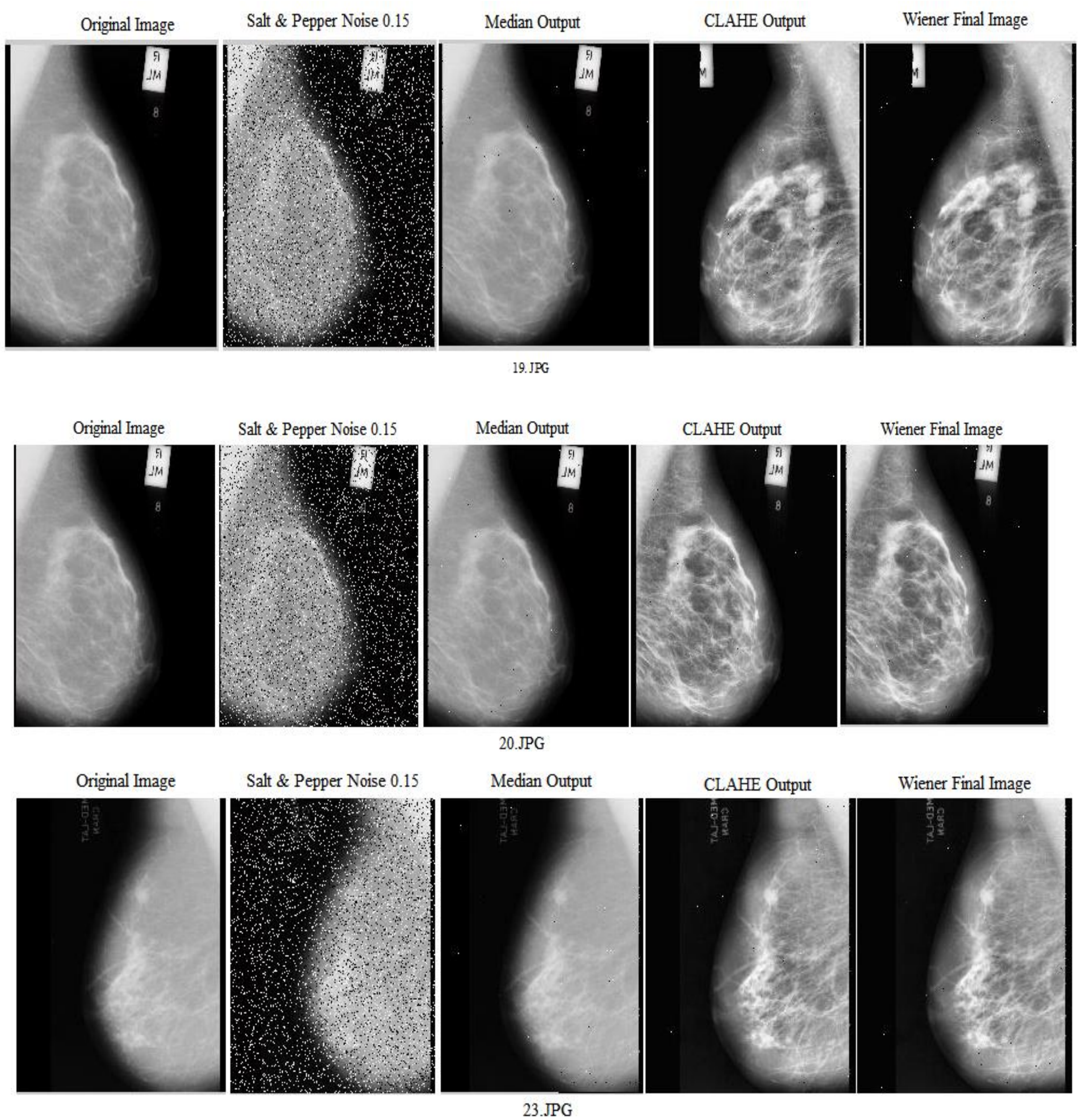


Figure 4.3: The Results When the Salt &Pepper is 0.1

3. The Output image when the salt &pepper is 0.1 is shown in figure 4.4.

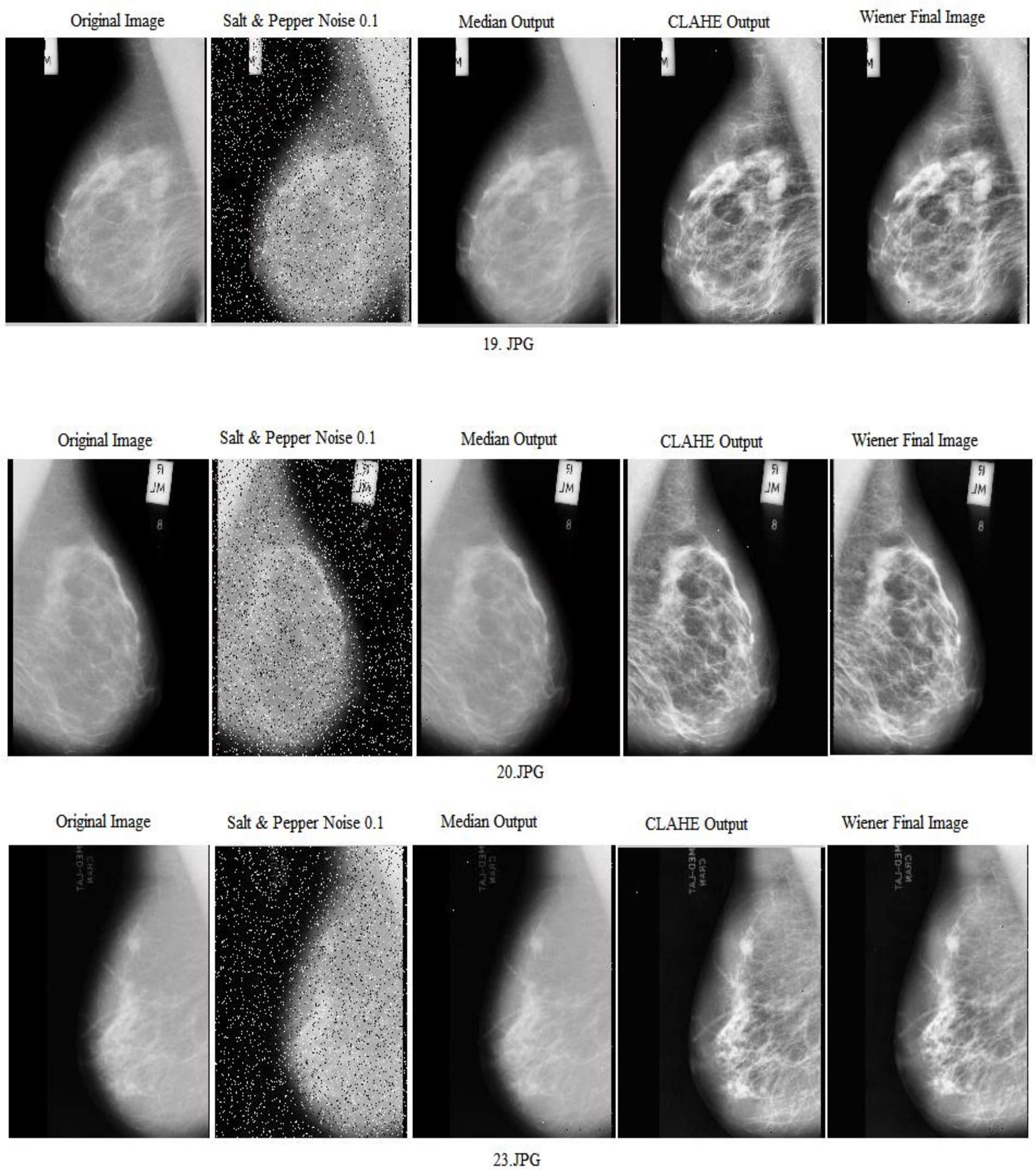


Figure 4.4: The Results When the Salt &Pepper is 0.1 db

It can be concluded from all images that the research technique is succeeded in enhancing the image quality. The median filter in the first stage removes most of the salt and pepper noise. The CLAHE in the second stage enhances the overall image contrast dramatically. The wiener filter impact is not clearly shown on the images but some of the distorted edges in the output images of the CLAHE are enhanced slightly as shown in figure 4.5.

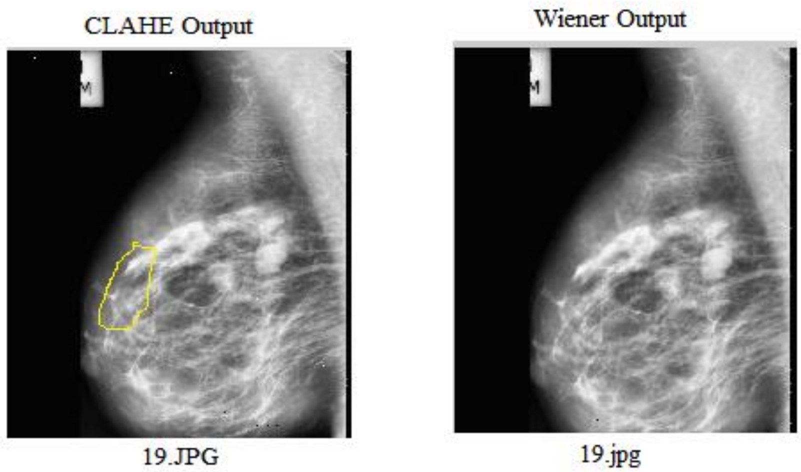


Figure 4.5: Wiener Enhancement

4.5.2 PSNR and MSE

The results of each stage in terms of PSNR and MSE are separated in tables 4.1, and 4.2, in order to facilitate the comparison process between the stages. The results are based on the images that subjected to different noise densities. The PSNR and MSE of the images corrupted with various noise densities is shown in table 4.3. The histogram of one image in various stages is shown in figure 4.6.

Table 4.1: PSNR and MSE of Median Filter

Filter Name	Noise	Image	MSE	PSNR
Median Filter	0.05	Mdb0.019	1.2781e+03	39.2937
		Mdb0.20	1.2834e+03	39.2527
		Mdb0.23	1.3262e+03	38.9248
	0.1	Mdb0.019	2.5377e+03	32.4351
		Mdb0.20	2.5856e+03	32.2483
		Mdb0.23	2.6518e+03	31.9955
	0.15	Mdb0.019	3.8011e+03	28.3948
		Mdb0.20	3.8369e+03	28.3012
		Mdb0.23	4.0064e+03	27.8689

Table 4.2: PSNR and MSE of Wiener Filter

Filter Name	Noise	Image	MSE	PSNR
Wiener Filter	0.05	Mdb0.019	1.5593	46.2014
		Mdb0.20	1.3103	46.9572
		Mdb0.23	1.1630	47.4750
	0.1	Mdb0.019	1.7233	45.7671
		Mdb0.20	1.4583	46.4923
		Mdb0.23	1.2885	47.0299
	0.15	Mdb0.019	2.0380	45.0389
		Mdb0.20	1.7699	45.6514
		Mdb0.23	1.5667	46.1809

Table 4.3: PSNR and MSE of Noise Image

Salt & Pepper Noise	Image	MSE	PSNR
0.05	Mdb0.019	1.2696e+03	39.3605
	Mdb0.20	1.2928e+03	39.1793
	Mdb0.23	1.3279e+03	38.9121
0.1	Mdb0.019	2.5325e+03	32.4556
	Mdb0.20	2.5708e+03	32.3056
	Mdb0.23	2.6425e+03	32.0305
0.15	Mdb0.019	3.7864e+03	28.4337
	Mdb0.20	3.8671e+03	28.2226
	Mdb0.23	3.9853e+03	27.9217

It can be noticed from tables 4.1 and 4.2 and in comparison with Table 4.3 that the restoration results for images corrupted by Salt and Pepper with various noise densities are better. The output of the wiener filter represents the final output of the research technique that has proved its ability in decreasing the MSE and increasing the PSNR, which is an indication of high images quality.

4.5.3 Contrast Histogram

Contrast limited adaptive histogram equalization CLAHE is applied to the mammogram images. The basic idea of method is to adjust the histogram of input image to a uniform one. A narrow contrast histogram indicates a low-contrast image (Morrow et al., 1992). It can be seen from the contrast histogram graph in figure 4.6, before using the CLAHE, that the image contrast is not uniform. After applying the CLAHE, the input image histogram is distributed uniformly.

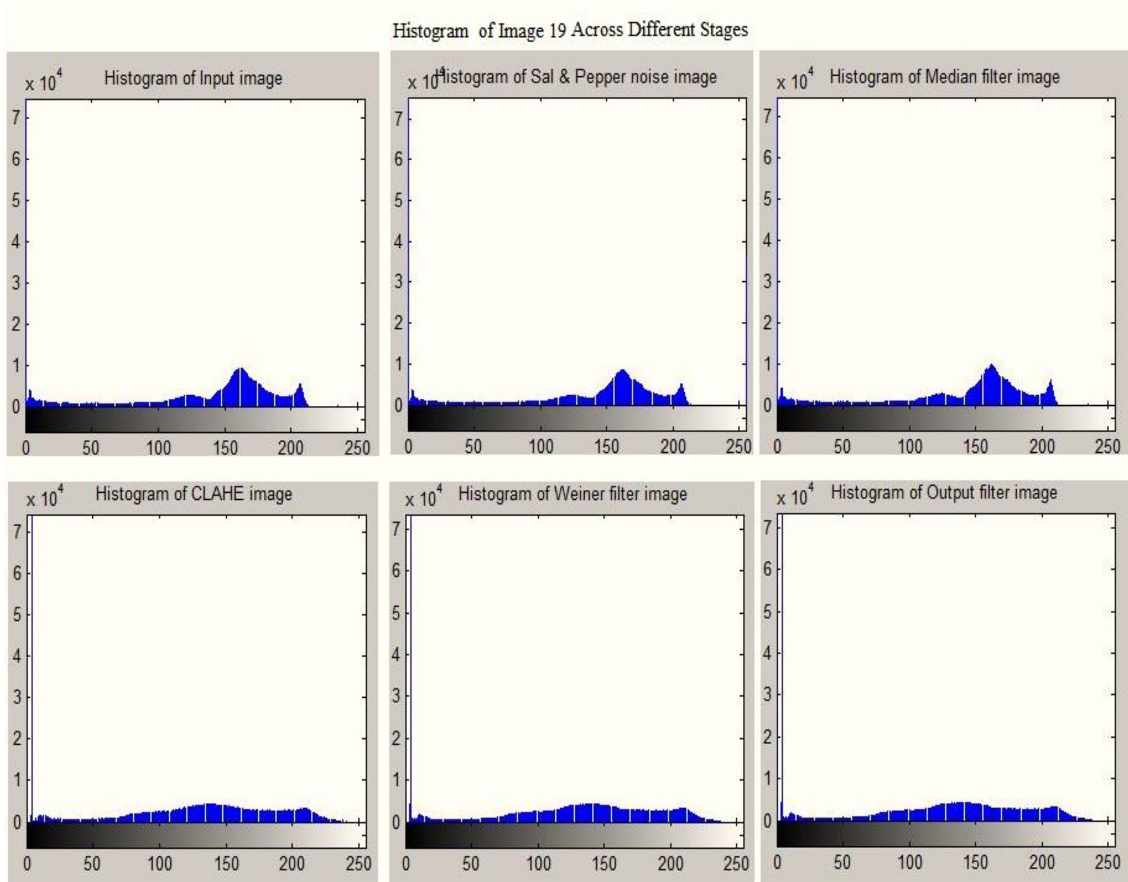


Figure 4.6: Contrast Histogram of Image 19 in Various Stages

4.6 First Comparison.

To evaluate the research technique performance, we compare the output of the research technique with the output of the median and wiener filters separately. The mammogram image number 19 is corrupted with Salt and Peppers noise with the same noise densities 0.05, 0.1, and 0.15 and applied to the research technique, median and wiener filters. The performance is quantified in terms of MSE and PSNR as shown in table 4.4.

Table 4.3: PSNR and MSE of Noise Image

Salt & Pepper Noise	Image	MSE	PSNR
0.05	Mdb0.019	1.2696e+03	39.3605
	Mdb0.20	1.2928e+03	39.1793
	Mdb0.23	1.3279e+03	38.9121
0.1	Mdb0.019	2.5325e+03	32.4556
	Mdb0.20	2.5708e+03	32.3056
	Mdb0.23	2.6425e+03	32.0305
0.15	Mdb0.019	3.7864e+03	28.4337
	Mdb0.20	3.8671e+03	28.2226
	Mdb0.23	3.9853e+03	27.9217

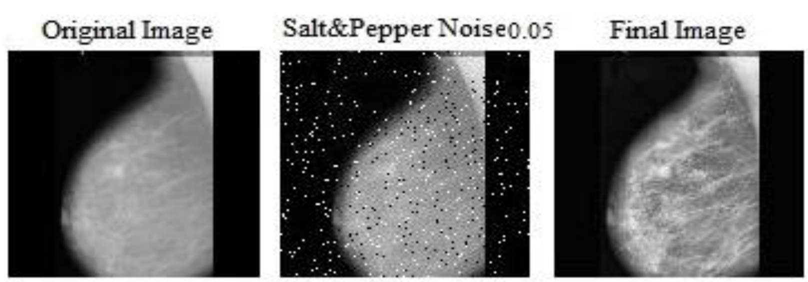
It is clear from the table 4.3 that the research technique has better performance than the separated Median and Wiener filters, where it achieves High PSNR and low MSE. In addition, it is clear that the median filter highly surpasses the wiener filter in removing Salt and Pepper noise

4.7 Second Comparison

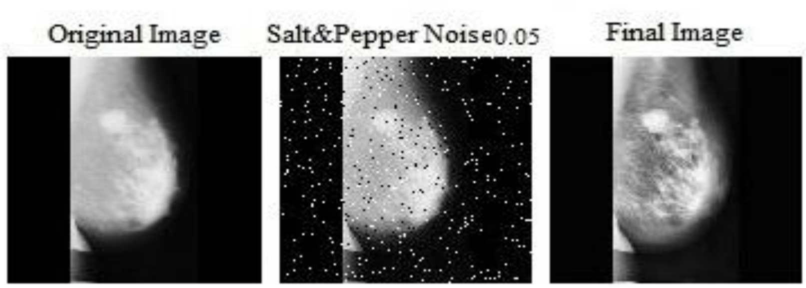
For more performance test, we compare the research results with the results of Ramani et al. research in 2013. They used three images from the same database of digital mammograms MIAS in their research. The images were corrupted with three types of noise: Salt and Pepper, Gaussian, and Speckle. Images denoising were done by using different filters namely average filter, adaptive median filter, average or mean filter, and wiener filter.

Three images corrupted with Salt and Pepper noise are used in the comparison. Ramani and his colleagues did not mention the Salt and Pepper noise density used in their research. Therefore, two noise densities 0.05 & 0.1 are used in the comparison with their results for more validation. The output images of the research technique are shown in figure 4.7.

mdb001.jpg



mdb155.jpg



mdb 322.jpg

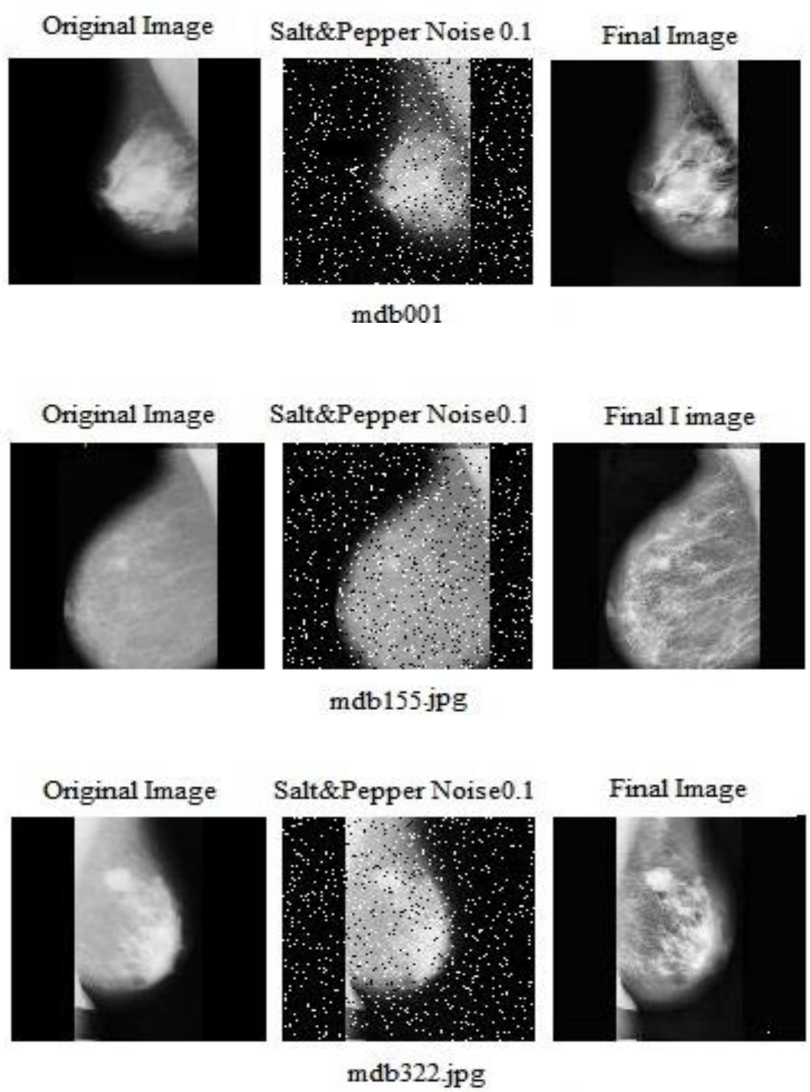


Figure 4.7: The Research Technique Results

The results of comparison in terms of PSNR between the research technique and the different filters of Ramani et al. are shown in table 4.5.

Table 4.5: Comparison Results with Different Filters

Filter Name	**Noise type**	**Image**	**PSNR**
Median Filter	Salt & pepper	Mdb001	30.5837
		Mdb155	30.1250
		Mdb322	30.9474
Weiner Filter		Mdb001	29.6526
		Mdb155	30.1001
		Mdb322	30.4095
Adaptive Median Filter		Mdb001	39.8323
		Mdb155	35.9657
		Mdb322	36.1147
Mean Filter		Mdb001	33.2336
		Mdb155	31.9987
		Mdb322	32.2944
Research Technique	Noise 0.05	Mdb001	50.3348
		Mdb155	46.3315
		Mdb322	49.1129
	Noise 0.1	Mdb001	49.8335
		Mdb155	45.8638
		Mdb322	48.7010

It can be observed from the table 4.5 that the adaptive median filter achieves higher PSNR when comparing with other filters, which means that its output images are of high quality. However, comparing with the research technique, its results are modest. The research technique achieves higher PSNR comparing with all filters, which reveals its ability to result a high quality images. Effective denoising can enhance images clarity for human viewing and features extraction, which increases the probability of early detection of breast cancer

4.8 Summary

The research proposed technique encompasses two stages filtering using median and wiener filters and one stage of contrast enhancement using CLAHE. The evaluation of the performance is measured by PSNF and MSE for the filters and by contrast histogram for the CLAHE. The output of the research technique is compared with the output of each stage and with the median and wiener filters separately. The results show better performance of the research technique compared with others.

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

5.1 Introduction

Numerous studies indicated that breast cancer early detection with mammography improve the chances of treatment and helps to save lives. A major problem with mammography concerns the visual detection of early signs of breast cancer that might be difficult particularly in dense breast tissue (Shen, 2013). Researchers have developed many image enhancement techniques to enhance the mammogram images quality. The effective technique is the one who has the ability to improve the mammogram images contrast without increasing noise. However, it is not easy to achieve this target.

5.2 Conclusions

The research proposed a technique for enhancing mammogram images to simplify the diagnosing of breast cancer. The technique aims to enhance the contrast of the mammogram images without boosting noise. Therefore, noise removal and contrast enhancement have been performed. The described technique has been tested on many mammographic images taken from the digital mammography database of Mammography Image Analysis Society (MIAS). All the images are corrupted by Salt and Pepper noise with different densities. Noise removal is performed through two stages by utilizing median and wiener filters and contrast enhancement is performed through one stage by CLAHE. Noise removal is quantified by using PSNR and MSE and contrast is evaluated by histogram. MATLAB 2010 software package is used to calculate the results.

Through the application of the research technique, it proves its ability in enhancing all the mammogram images quality. During the application, many conclusions have been concluded such as:

1. The median filter succeeded in removing most of the salt and pepper noise from the mammogram images.
2. The CLAHE has distributed the image contrast normally but it caused some blurring in some edges.
3. The wiener filter has succeeded to some extent in removing some of the distortions of edges of the CLAHE output images.
4. The performance of the research technique is better than the performance of each stage in terms of high PSNR and low MSE.
5. The performance of the research technique is better than the performance of the median and wiener filters separately in terms of high PSNR and low MSE.

6. The median filter is better than the wiener in removing Salt and Pepper noise as indicated by previous researches in the literature.
7. The research technique is better than mean and adaptive median filters in terms of PSNR.

Generally, it is not easy to achieve high quality image because each filer and the CLAHE has side effects. The median filter is not completely removing the noise and the CLAHE unified the image contrast but caused some edges blurring. While the effect of the wiener filter is moderated in repairing the distortion.

5.3 Research Limitations

The main limitation is that the noise was added to the images by the MATLAB, which means that it is uniform noise and not real, which could easily be removed by the MATLAB algorithms. Therefore, the research technique performance cannot be fully evaluated.

5.4 Future Work

The performance of the research technique will be evaluated in removing the same noise from images corrupted with real Salt and Pepper noise. It will also be evaluated with other type of noise like Speckle, Poisson and Gaussian.

REFERENCES

Al-amri, S. S., Kalyankar, N. V., & Khamitkar, S. D. (2010). A comparative study of removal noise from remote sensing image. arXiv preprint arXiv:1002.1148.

American Cancer Society. Mammograms and other Breast Imaging Procedures. Retrieved on May 2013 from: http://www.cancer.org/treatment/understandingyourdiagnosis/examsandtestdescriptions/mammogramsandotherbreastimagingprocedures/mammograms-and-other-breast-imaging-procedures-what-is-mammogram

Arastehfar, S., Pouyan, A. A., & Jalalian, A. (2013). An Enhanced Median Filter for Removing Noise from MR Images. Journal of AI and Data MiningJournal of AI and Data Mining, 1(1), 13-17.

Bandyopadhyay, S. K. (2011). Diagnosis of Breast Abnormalities in Mammographic Image. IJCST, 2(1).

Bozek, J., Delac, K., & Grgic, M. (2008). Computer-aided detection and diagnosis of breast abnormalities in digital mammography. In ELMAR, 2008. 50th International Symposium (Vol. 1, pp. 45-52). IEEE.

Bozek, J., Mustra, M., Delac, K., & Grgic, M. (2009). A survey of image processing algorithms in digital mammography. In Recent Advances in Multimedia Signal Processing and Communications (pp. 631-657). Springer Berlin Heidelberg.

Byng, J. W., Boyd, N. F., Fishell, E., Jong, R. A., & Yaffe, M. J. (1996). Automated analysis of mammographic densities. Physics in medicine and biology, 41(5), 909.

Cheng, H. D., & Xu, H. (2002). A novel fuzzy logic approach to mammogram contrast enhancement. Information Sciences, 148(1), 167-184.

Chevalier, M., Leyton, F., Tavares, M. N., Oliveira, M., da Silva, T. A., & Peixoto, J. E (2012). Image Quality Requirements for Digital Mammography in Breast Cancer Screening. Imaging of the Breast - Technical Aspects and Clinical Implication, Dr. Laszlo Tabar (Ed.), ISBN: 978-953-51-0284-7, InTech

Christian, S. (2011). Analysis of Contrast Enhancement Methods for Infrared Images. Master Thesis. Faculty of California Polytechnic State University ,San Luis Obispo

Dos Santos Romualdo, L. C., da Costa Vieira, M. A., & Schiabel, H. (2009, October). Mammography images restoration by quantum noise reduction and inverse MTF filtering. In

Computer Graphics and Image Processing (SIBGRAPI), 2009 XXII Brazilian Symposium on (pp. 180-185). IEEE

Dos Santos Teixeira R. F. (2012). Computer Analysis of Mammography Images To Aid Diagnosis. Monography, Universidade do Porto

Eltoukhy M. M., Faye I., Samir B. B. (2009). Using curvelet transform to detect breast cancer in digital mammogram. In Signal Processing & Its Applications,. CSPA 2009. 5th International Colloquium on (pp. 340-345). IEEE

Gopal , G. D. (2008) . Mammogram Image Segmentation Using Fuzzy Hybrid with Particle Swarm Optimization (PSO). International Journal of Engineering and Innovative Technology (IJEIT), Volume 2 (6)

Hargaš, L., Hrianka, M., & Duga, A. (2003) Noise image restoration by spatial filters. In Radioelektronika 2003: 13th international Czech-Slovak scientific conference (pp. 376-379).

Hosseini, H., & Marvasti, F. (2011). Fast Impulse Noise Removal from Highly Corrupted Images. arXiv preprint arXiv:1105.2899.

Ilango, G., & Marudhachalam, R. (2011). New hybrid filtering techniques for removal of Gaussian noise from medical images. ARPN Journal of Engineering and Applied Sciences, 6(2), 8-12.

Kaur, J., & Gupta, P. (2012). Fuzzy Logic based Adaptive Noise Filter for Real Time Image Processing Applications. International Journal of Computer Science Issues(IJCSI), 9(4).

Kaur, M., Kaur, J., & Kaur, J. (2011). Survey of contrast enhancement techniques based on histogram equalization. International Journal of Advanced Computer Science and Applications, 2(7), 138-141.

Khireddine, A., Benmahammed, K., & Puech, W. (2007). Digital image restoration by Wiener filter in 2D case. Advances in Engineering Software, 38(7), 513-516.

Kim, J. K., Park, J. M., Song, K. S., & Park, H. W. (1997). Adaptive mammographic image enhancement using first derivative and local statistics. Medical Imaging, IEEE Transactions on, 16(5), 495-502.

Kwok S. M., Chandrasekhar R.A., Attikiouzel Y., Rickard M.T. (2004). Automatic Pectoral Muscle Segmentation on Mediolateral Oblique View Mammograms. Medical Imaging, IEEE Transactions on, 23 (9), pp.1129, 1140

Krishnan, M. H., & Viswanathan, R. (2013). A New Concept of Reduction of Gaussian Noise in Images Based on Fuzzy Logic. Applied Mathematical Sciences, 7(12), 595-602.

Krutsch, R., & Tenorio, D. (2011). Histogram Equalization. Free scale Semiconductor, Document Number AN4318, Application Note.

Kumar, H., Amutha. S., Babu, R. (2012) . Enhancement of Mammographic Images using Morphology and Wavelet Transform.Int.J.Computer Techology & Applications,Vol 3 (1),192-198

Kumar, N. Karambir & Sing, K. (2011). Wiener Filter Using Digital Image Restoration. International Journal of Electronics Engineering, 3 (2), pp. 345– 348

Kundra, E. H., Verma, E. M., & Aashima, E. (2011). Filter for removal of impulse noise by using fuzzy logic. International Journal of image processing (IJIP), 3(5), 195.

Laine, A.; Fan, J.; Wuhai Yang, "Wavelets for contrast enhancement of digital mammography," Engineering in Medicine and Biology Magazine, IEEE , vol.14, no.5, pp.536,550, 1995

Mahesh, T. R., Prabhanjan, S., Vinayababu, M. (2010). Noise Reduction by Using Fuzzy Image Filtering. Journal of Theoretical and Applied Information Technology, Vol 15, No. 2

Maheswari, D., & Radha, V. (2010). Noise removal in compound image using median filter. International Journal on Computer Science and Engineering, 2(04), 1359-1362.

Maini, R., & Aggarwal, H. (2010). A comprehensive review of image enhancement techniques. arXiv preprint arXiv:1003.4053.

Maitra, I. K., Nag, S., & Bandyopadhyay, S. K. (2012). Technique for preprocessing of digital mammogram. Computer methods and programs in biomedicine, 107(2), 175-188.

Mayo, P., Rodenas, F., & Verdu, G. (2004, September). Comparing methods to denoise mammographic images. In Engineering in Medicine and Biology Society, 2004. IEMBS'04. 26th Annual International Conference of the IEEE (Vol. 1, pp. 247-250). IEEE.

Mencattini A., Salmeri M., Lojacono R., Frigerio M., Caselli F. (2008). Mammographic images enhancement and denoising for breast cancer detection using dyadic wavelet processing. Instrumentation and Measurement, IEEE Transactions on, 57(7), 1422-1430

Morrow, W. M., Paranjape, R. B., Rangayyan, R. M., & Desautels, J. E. L. (1992). Region-based contrast enhancement of mammograms. Medical Imaging, IEEE Transactions on, 11(3), 392-406.

Naseem M. T., Sulong G. B., Jaffar M. A. (2012). MRT letter: Quantum noise removal and classification of breast mammogram images. Microscopy Research and Technique, 75(12), 1609-1612

Naveed N., Jaffar M. A., Choi T. S. (2011). MRT letter: Segmentation and texture-based classification of breast mammogram images. Microscopy research and technique, 74(11), 985-987

Patel, V. K., Uvaid, S., & Suthar, A. C. (2012). Mammogram of Breast Cancer detection Based using Image Enhancement Algorithm. Int. J. Emerg. Technol. Adv. Eng, 2(8), 143-147.

Patidar P., Gupta M., Srivastava S., Nagawat A. K. (2010). Image De-noising by Various Filters for Different Noise. International Journal of Computer Applications, 9(4)

Pizurica, A. (2002). Image denoising using wavelets and spatial context modeling (Doctoral dissertation, Gent University).

Ponraj, D. N., Jenifer, M. E., Poongodi, P., & Manoharan, J. S. (2011). A Survey on the Preprocessing Techniques of Mammogram for the Detection of Breast Cancer. Journal of Emerging Trends in Computing and Information Sciences, 2(12), 656-664.

Prakash, K. B., Babu, R. V., & VenuGopal, B. (2011) Image Independent Filter for Removal of Speckle Noise. International Journal of Computer Science, 8(3),No 3

Rajkumar, K. K., & Raju, G. (2011). A comparative study on classification of mammogram images using different wavelet transformations. International Journal of Machine Intelligence, 3(4).

Ramani, R., Vanitha, N. S., & Valarmathy, S. (2013). The Pre-Processing Techniques for Breast Cancer Detection in Mammography Images. International Journal of Image, Graphics & Signal Processing, 5(5).

Rangarajan, R., Venkataramanan, R., & Shah, S. (2002). Image denoising using wavelets. Wavelet and Time Frequencies.

Rose C. J. (2005). Statistical Models of Mammographic: Texture and Appearance. PhD Thesis. Faculty of Medical and Human Sciences, University of Manchester

Ruikar, S. D., & DOye, D. D. (2011). Wavelet Based Image Denoising Technique. International Journal of Advanced Computer Science and Applications, 2(3), 49-53.

Sangeetha, T. A., & Saradha, A. (2012). An Efficient Way to Enhance Mammogram Image in Transformation Domain. International Journal of Computer Applications, 60(2).

Sangeetha, T. A., Saradha, A. (2013). An Efficient Technique to Enhance Mammogram Image Using Curvelet Transform. International Journal of Computer Science Engineering and Information Technology Research (IJCSEITR), Vol. 3, Issue 1, Mar 2013, 155-164

Satheesh, S., & Prasad, K. V. S. V. R. (2011). Medical image denoising using adaptive threshold based on contourlet transform. arXiv preprint arXiv:1103.4907.

Shen, H. (2013). A novel image enhancement method for mammogram images. master thesis, Western Carolina University.

Shinde, B., Mhaske, D., Patare, M., Dani, A. R., & Dani, A. R. (2012). Apply Different Filtering Techniques To Remove The Speckle Noise Using Medical Images. International Journal of Engineering Research and Applications, 2(1), 1071-1079.

Subashini, T. S., Ramalingam, V., & Palanivel, S. (2010). Automated assessment of breast tissue density in digital mammograms. Computer Vision and Image Understanding, 114(1), 33-43.

Subr, K., Majumder, A., & Irani, S. (2005). Greedy algorithm for local contrast enhancement of images. In Image Analysis and Processing–ICIAP 2005 (pp. 171-179). Springer Berlin Heidelberg.

Talha, M., Sulong, G. B., & Alarifi, A.(2011). Enhanced Breast Mammograms Classification using Bayesian Classifier. King Saud University

Urbana Ivy B.P., Saranya J., Sabatini S. (2012). Diagnosis of Breast Cancer. IJCSET. Vol 2, Issue 2,865-868

Van De Ville, D.; Nachtegael, M.; Van der Weken, Dietrich; Kerre, E.E.; Philips, W.; Lemahieu, I. (2003). "Noise reduction by fuzzy image filtering," Fuzzy Systems, IEEE Transactions on, vol.11, no.4, pp.429, 436, Aug. 2003

Veldkamp, W. J., & Karssemeijer, N. (2000). Normalization of local contrast in mammograms. Medical Imaging, IEEE Transactions on, 19(7), 731-738. Chicago

Vij, K., & Singh, Y. (2009). Enhancement of images using histogram processing techniques. Int. J. Comp. Tech. Appl, 2(2), 309-313.Chicago

Yoon, H., Han, Y., & Hahn, H. (2009). Image contrast Enhancement based Sub-histogram Equalization Technique without over-equalization Noise. World Academy of Science, Engineering and Technology, 50, 2009.

Zhang, X., Homma, N., Goto, S., Kawasumi, Y., Ishibashi, T., Abe, M., ... & Yoshizawa, M. (2013). A Hybrid Image Filtering Method for Computer-Aided Detection of Microcalcification Clusters in Mammograms. Journal of Medical Engineering, 2013.

Zhou C., Chan H.P., Petrick N., Helvie M.A., Goodsitt M.M., Sahiner B., Hadjiiski L. (2001). Computerized image analysis: estimation of breast density on mammograms. Medical Physics 28 (6), pp. 1056–1069