CONTRAST ENHANCEMENT OF MAMMOGRAMS FOR BREAST CANCER DETECTION

Project Report submitted in partial fulfillment of the requirement for the degree of

Bachelor of Technology.

In

Electronics and Communication Engineering

under the Supervision of

Mr. JITENDRA VIRMANI

By

YASHA PORWAL - 101126

to

May 2014

Jaypee University of Information and Technology

Waknaghat, Solan – 173234, Himachal Pradesh

JAYPEE UNIVERSITY OF INFORMATION TECHNOLOGY
(Established under the Act 14 of Legislative Assembly of Himachal Pradesh)
Waknaghat, P.O. Domehar Bani. Teh. Kandaghat, Distt. Solan- 173234(H.P)
Phone: 01792-245367, 245368,245369
Fax-01792-245362

DECLARATION

I hereby declare that the work reported in the B. Tech thesis entitled "**Contrast Enhancement Of Mammograms For Breast Cancer Detection"** submitted by "**Ms. Yasha Porwal"** at Jaypee University Of Information Technology, Waknaghat is an authentic record of our work carried out under the supervision of **Mr. Jitendra Virmani** This work has not been submitted partially or wholly to any other university or institution for the award of this or any other degree or diploma.

Ms. Yasha Porwal (101126)
Department of electronics and communication engineering
Jaypee University of Information Technology (JUIT)
Waknaghat, Solan – 173234, India

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DEFINITION	ABBREVIATION
Breast Self Examination	BSE
Clinical Breast Examination	CBE
Craniocaudal	CC
The American College Of Radiology (Acr)	ACR
Mediolateral-Oblique	MLO
Breast Imaging Reporting And Data System	BI-RADS
Region Of Interest	ROI
Mammogram Image Analysis Society	MINI MIAS
Unsharp Masking	UN
Histogram Equalization	HE
Adaptive Histogram Equalization	AHE
Structuring Element	SE
Laplacian Pyramids	LP
Wavelet Transform	WT
Discrete Wavelet Transform	DWT
Low Low	LL
Low High	LH
High Low	HL
High High	HH
Dyadic Wavelet Transform	DyWT
Contourlet Transform	CT
Directional Filter Banks	DFB
Fuzzy Image Processin	FIP

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Phone: 01792-245367, 245368,245369
Fax-01792-245362

CERTIFICATE

This is to certify that project report entitled **"Contrast Enhancement Of Mammograms For Breast Cancer Detection"**, submitted by **Yasha Porwal** in partial fulfillment for the award of degree of Bachelor of Technology in Electronics and Communication Engineering to Jaypee University of Information Technology, Waknaghat, Solan has been carried out under my supervision.

This work has not been submitted partially or fully to any other University or Institute for the award of this or any other degree or diploma.

Date: May 15,2014 **JitendraVirmani**

Asstt. Prof. ECED

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I would like to express my deep gratitude to Professor Jitendra Virmani, my project supervisor, for his patient guidance, enthusiastic encouragement and useful critiques of this project. I have to appreciate the guidance given by other supervisor as well as the panel, whose comments and advices helped in improving the presentation.

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A special thanks to Jaypee University of Information Technology that provided us with an opportunity to undertake such a task.

Date: May 15, 2014 **YashaPorwal**

101126

MOTIVATION

Breast cancer is the most common cancer among women over 40 years. Studies have shown that early detection and appropriate treatment of breast cancer significantly increase the chances of survival. They have also shown that early detection of small lesions boosts prognosis and leads to a significant reduction in mortality.

Mammography is in this case the best diagnostic technique for screening. However, the interpretation of mammograms is not easy because of small differences in densities of different tissues within the image. This is especially true for dense breasts. This analysis could provide radiologists a better understanding of stereotypes and provides, if it is detected at an early stage, a better prognosis inducing a significant decrease in mortality.

ABSTRACT

Breast cancer is known to be the most common form of cancer in women. Every 1 in 10 woman is diagnosed with the same. It has become one of the main diseases according to published statistics over the past 50 years. Until now, however, it is not considered that there have been any useful ways to avoid breast cancer, as its causes are still unknown. Studies have shown its survival has improved in the recent years as early detection and appropriate treatment of breast cancer significantly increased the chances to live. The typical diagnostic signs such as microcalcifications and masses are difficult to detect because mammograms are low-contrast and noisy images and can't prove that an abnormal area is cancer. Therefore, image denoising and enhancement becomes necessary for better understanding of stereotypes.

This project reviews the recent enhancement techniques that have been explored and exist in the literature. At the enhancement stage, the geometric information is analyzed to increase the contrast of the edges. Denoising and enhancement stages can be applied together for the enhancement of mammogram images in various ways. Each method is classified, analyzed, and compared against other approaches. To examine the accuracy of the mammogram enhancement techniques, the sensitivity and specificity of the approaches is presented and compared where applicable. This project will provide anatomy for the available approaches and highlights the best available enhancement.

Jitendra Virmani

Asstt. Prof. ECED

OBJECTIVE

I. Data Collection and Understanding the Data
II. Data preprocessing
III. Enhancement of the processed data
IV. Comparison of the enhancement techniques

This Includes:

I. Comparison and analysis of the available mammogram enhancement algorithms.
II. The comparison will provide radiologists the best technique to enhance digital mammograms with masses.

Chapter 1

INTRODUCTION

Globally, breast cancer ranks fifth most common cause of cancer deaths and leading cause of cancer affecting women. 1 out of every 10 women has suffered from this in her lifetime. Rare cases of the same are seen in men too. However, no study has been able to identify with certainty why every year, one million breast cancer cases are discovered and 400 000 women die [1]. If detected early, breast cancer is easier to treat, with fewer risks and reduces mortality by 25%. There are several ways in which early detection can be achieved which comprises of **breast self examination (BSE), clinical breast examination (CBE), imaging** or **mammography,** and **surgery.**

Among the mentioned, Mammography has proved to be the sensitive method for early detection of masses and abnormalities. The blurriness of mammograms makes it difficult to achieve accurate results. Thus proper enhancement of the low-contrast and noisy images becomes uttermost important. The goal of this project is to provide a comprehensive review, comparison, and analysis of the available mammogram enhancement algorithms. The rest of this paper is organized as follows: section 2 presents details of mammogram image enhancement techniques, and section 3 evaluates the proposed approaches. Finally, section 4 presents the conclusion and the future work.

1.1 Mammography

Various imaging methods have emerged in recent years, including ultrasound imaging, X-ray imaging, and magnetic resonance imaging. Mammography is the most helpful technique for detection of early stage breast cancer and helps to decrease the rate of mortality by up to 25 percent. Also, it is a type of imaging based on a low dose of X-rays for breast examination. However, the interpretation of mammograms is not easy because of small differences in densities of different tissues within the image. This is especially true for dense breasts. This analysis could provide radiologists a better understanding of stereotypes and provides, if it is detected at an early stage, a better prognosis inducing a significant decrease in mortality.

A **mammogram** is an X-ray, particularly suited to woman breast to detect nodules whose presence may indicate the existence of breast cancer. It can detect up to 85 to 90 percent of all cancers allowing doctors to see if there is an abnormality in the breast.

Nonetheless, many suspicious findings on mammograms are benign. The most important mammographic signs of malignancy are masses and microcalcifications. The benign biopsy rate for mammographic ally suspicious, non - palpable breast masses is about 70%–80. 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:

I. Masses
II. Microcalcifications.

1.2 Mammogram Enhancement

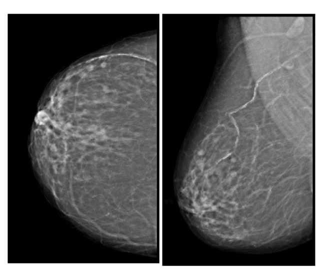
Due to the human factor involved in the screening process, detection of suspicious abnormalities is prone to a high degree of error. Although the mammogram is one of the most robust techniques for early discovery of breast cancer, the mammogram is low contrast which can cause difficulties in the detection of small masses and microcalcifications which are indirect signs of malignancy. Studies have shown that radiologists have an error rate between 10%–30% for detection of cancer in screening studies. Misinterpretation of breast cancer signs result in 52% of the errors and 43% of the errors are caused due to overlooking signs in abnormal scans. As a result of this error rate, biopsies are frequently performed on benign lesions, resulting in unwarranted expenditure and anxiety for the patient involved. The cost associated with errors due to misclassification of mammograms is considerable. This is because of the fact that false negatives are a huge problem in screening mammography as early detection can reduce treatment cost, time and effectiveness to a great extent. False negatives affect all three parameters as early detection is not an option with an incorrect diagnosis.

1.3 Types of Mammography

Screening mammograms look for signs of cancer. Screening mammogram are x-ray exams of the breasts that are used for women who have no breast symptoms. The goal of a screening mammogram is to find breast cancer when it's too small to be felt by a woman or her doctor.

Diagnostic mammograms investigate possible problems. A woman with a breast problem (for instance, a lump or nipple discharge) or an abnormal area found in a screening mammogram typically gets a diagnostic mammogram. The diagnostic mammography examination is performed for symptomatic women who have an abnormality found during screening mammography.

During a diagnostic mammogram, additional pictures are taken to carefully study the area of concern. In most cases, special pictures are enlarged to make a small area of suspicious breast tissue bigger and easier to evaluate. Nowadays, in most hospitals the screen film mammography is being replaced with digital mammography in which the breast image is captured using a special electronic x-ray detector which converts the image into a digital mammogram for viewing on a computer monitor or storing. Each breast is imaged separately in craniocaudal (CC) view and mediolateral-oblique (MLO) view shown in Figure 1(a) and Figure 1(b), respectively. The American College of Radiology (ACR) Breast Imaging Reporting and Data System (BI-RADS) suggests a standardized method for breast imaging reporting. Terms have been developed to describe breast density, lesion features and lesion classification.



(a) (b)

Figure 1.1: Two basic views of mammographic image:
(a) craniocaudal (CC) view, (b) mediolateraloblique (MLO) view

1.4 Different Forms of Breast Abnormalities

There are several forms of abnormality that may affect breast tissue. These abnormalities are often classified into two families:

I. Opacities
II. Microcalcifications

1.4.1 Masses

Masses are defined as space-occupying lesions. They are characterized by their smooth boundaries, are often found in the thick regions of breast tissue, and come in different shapes such as speculated, ill-defined, circumscribed, and lobulated. The speculated masses are characterized by their star shaped and rough boundaries, while lobulated ones are distinguished with their irregular shapes. In contrast, the circumscribed masses are usually between 2-30mm in diameter with high density radiopaque. The variation between the background and intensities of the masses makes their visualization harder in a mammogram with microcalcifications. Therefore, the methods focused on the enhancement of masses should enhance the masses' features and texture

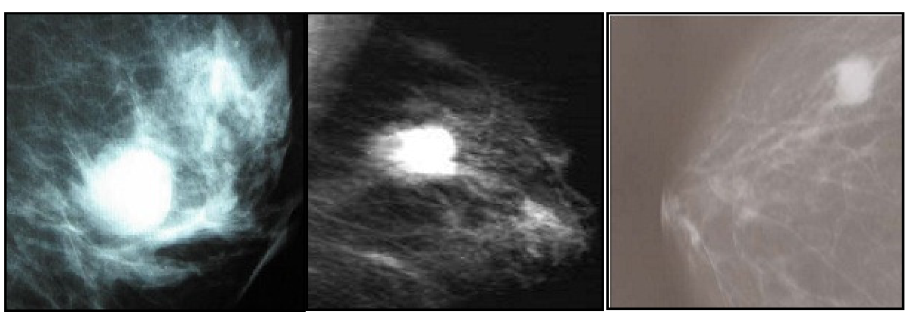


Figure 1.2: Masses

1.4.2 Microcalcifications

Microcalcifications are tiny deposits of calcium that appear as small bright spots in the mammogram. Although they have higher inherent attenuation properties, they cannot be distinguished from the high-frequency noise because of their small size. The average size of microcalcifications is about 0.3 mm.

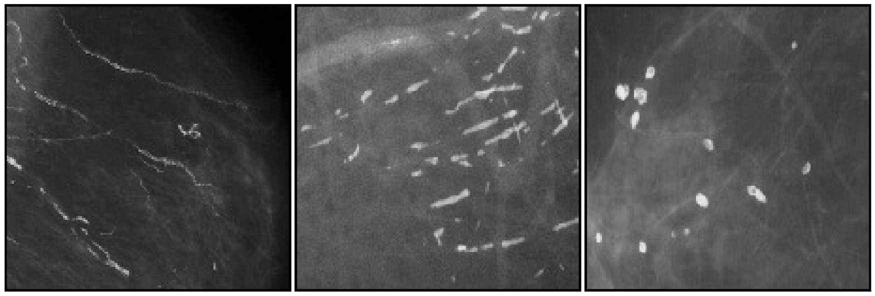
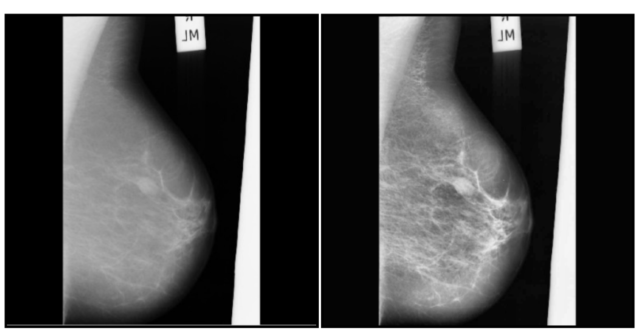


Figure 1.3: Microcalcifications

Two major concerns are false-negative results and false-positive interpretations. False-positives lead to unnecessary follow-up and biopsies performed on women with benign conditions. False-negatives will cause a delay in diagnosis and treatment, and allow early stage disease to progress to a more advanced stage with severe implications for survival rates. Though denoising and the enhancement of mammograms can help radiologists to precisely detect malignant microcalcifications at their early stage, it is a challenging task. On the other hand, the main difficulty with contrast enhancement is that, for an image, some areas are possibly under-enhanced while other areas may be over-enhanced. Under-enhanced images lead to false-negative results and over-enhanced ones will lead to false-positive interpretation.

Generally, mammogram enhancement contains contrast and intensity modifications, and the reduction of noise, filtering, or edge sharpening. Mammogram enhancement aims to make the boundaries of the region of interest (ROIs) or edges much sharper, or to enhance the contrast between the background and ROIs.



(a) **(b)**

Figure 1.4: (a) Original Mammogram (b) Enhanced Image

1.5 Types of Mammographic Masses

1.5.1 Benign

A benign mass is a mass of cells (tumor) that lacks the ability to invade neighboring tissue or metastasize. These characteristics are required for a tumor to be defined as cancerous and therefore benign tumors are non-cancerous.

They:

• can usually be removed

• do not come back in most cases

• do not spread to other parts of the body and the cells do not invade other tissues

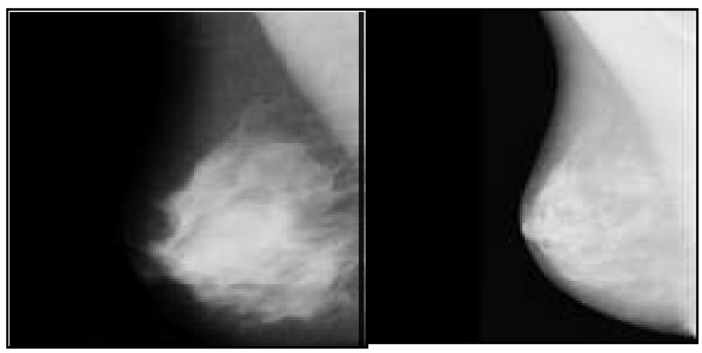


Figure 1.5: Benign masses

1.5.2 Malignant

Malignant neoplasm invades and destroy the surrounding tissue, may form metastases and eventually kill the host. Malignant tumors are cancerous.

They:

• can invade and damage nearby tissues and organs

• metastasize (cancer cells break away from a malignant tumor and enter the bloodstream or lymphatic system to form secondary tumors in other parts of the body)

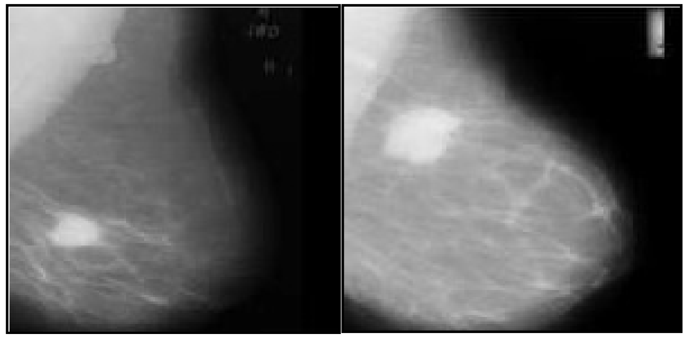


Figure 1.6: Malignant masses

Chapter 2

BASIC ENHANCEMENT TECHNIQUES

Wide range of image processing techniques has been developed for image enhancement, object localization, segmentation, restoration and classification.

Image enhancement processes consist of a collection of techniques that seek to improve the visual appearance of an image or to convert the image to a form better suited for analysis by a human or machine. Meanwhile, the term image enhancement is mean as the improvement of an image appearance by increasing dominance of some features or by decreasing ambiguity between different regions of the image.

Mammogram image enhancement is the process of manipulating mammogram images to increase their contrast and decrease the noise present in order to aid radiologists in the detection of abnormalities. The mammogram image having only two regions namely clustered micro calcifications region and a background tissue region. The methods used to manipulate mammogram images can be categorized into four main categories:

I. The conventional enhancement techniques
II. The region-based enhancement techniques
III. The feature-based enhancement techniques
IV. The fuzzy enhancement techniques

Conventional enhancing techniques are fixed neighborhood techniques and they are used to modify images based on global properties. The conventional enhancement techniques are mostly used to enhance masses in mammogram images.

Region-based methods enhance the contrast of mammogram features according to the regional properties. Region-Based techniques are used in segmentation. Similar to the conventional enhancement methods, the region-based enhancement methods are mostly used for the enhancement of masses.

Region detection techniques are three types such as

I. Local techniques
II. Global techniques
III. Splitting and merging techniques.

Local techniques means pixels are placed in a region based on their properties or their neighborhood properties.

Global techniques means pixels are grouped into regions based on the image pixel properties.

Splitting and merging techniques means these techniques use graph structures to represent regions and boundaries.

Feature based enhancement methods are those that are based on wavelet domain enhancement. By using the wavelet transform, it is possible to detect details that appear at different scales and selectively enhance them within different resolution levels. Feature based enhancement methods can be used to enhance both masses and micro-calcifications.

Fuzzy enhancement techniques are methods that apply fuzzy operators and properties to enhance mammogram features. Just like feature based enhancement, fuzzy enhancement methods can also be used to enhance masses and micro-calcifications.

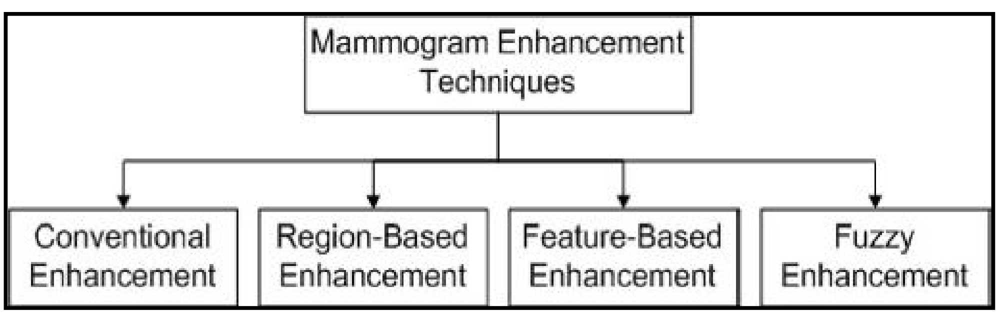


Figure 2.1: Categorizations of mammogram enhancement techniques

2.1 Image Acquisition

To access the real medical images for carrying out tests is a very difficult undertaking due to privacy issues and heavy technical hurdles. Mammograms are obtained from Mammogram Image Analysis Society (Mini MIAS) database containing 322 left and right breast images for a total of 161 patients are used in this project. All images containing speculated/circumscribed masses and a selection of normal types are considered. Supplied ground truth data for each image includes tissue type and regions of interest encompassing the abnormalities given in terms of a centroid and region radius. All images are digitized at a resolution of 1024x1024 pixels and at 8-bit grey scale level available in .pgm format.

2.2 Steps involved

I. Collection of mammographic images from Mini MIAS database
II. Converting .pgm images to .jpeg images
III. Applying proposed techniques

2.3 Mammogram Image Enhancement

2.3.1 Unsharp Masking

Unsharp Masking (UM) is one of the simplest contrast enhancement methods. In this method, the enhanced image $y(m,n)$ is acquired using the following mapping function from the original image $x(m,n)$:

$$y(m,n) = x(m,n) + \lambda z(m,n)$$

Where $z(m,n)$ is the output from the high pass filter that allows the high frequency signal to pass while switch off some signals with low frequencies.

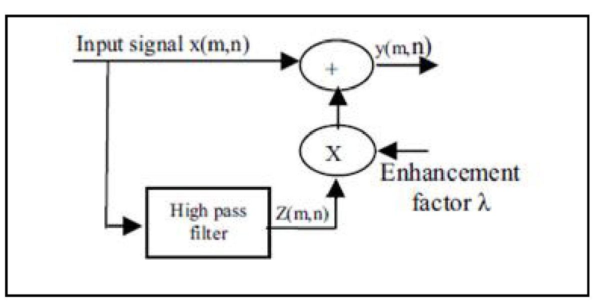
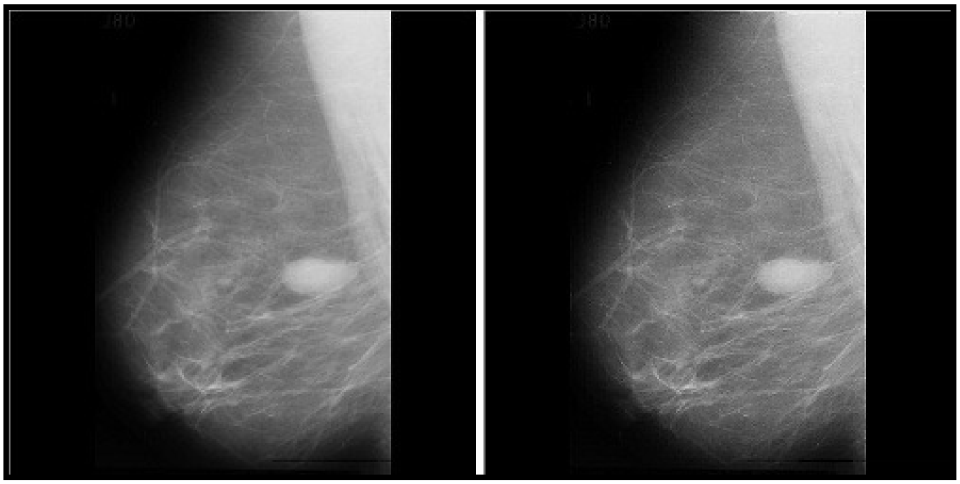


Figure 2.2: Block scheme for UM filter.



(a) **(b)**

Figure 2.3: (a) Original Image (b) Unsharped Image

2.3.2 Histogram Processing

Histogram is one of the essential statistical characteristic of an image as it is used to identify the distribution of intensity values of all image pixels. Figure 2.4 shows an 8 bit grayscale image and its corresponding histogram. A bin **h(i)** in a histogram can be defined as:

$h(i) = n_i$, where n_i is pixels number's with a gray value i.

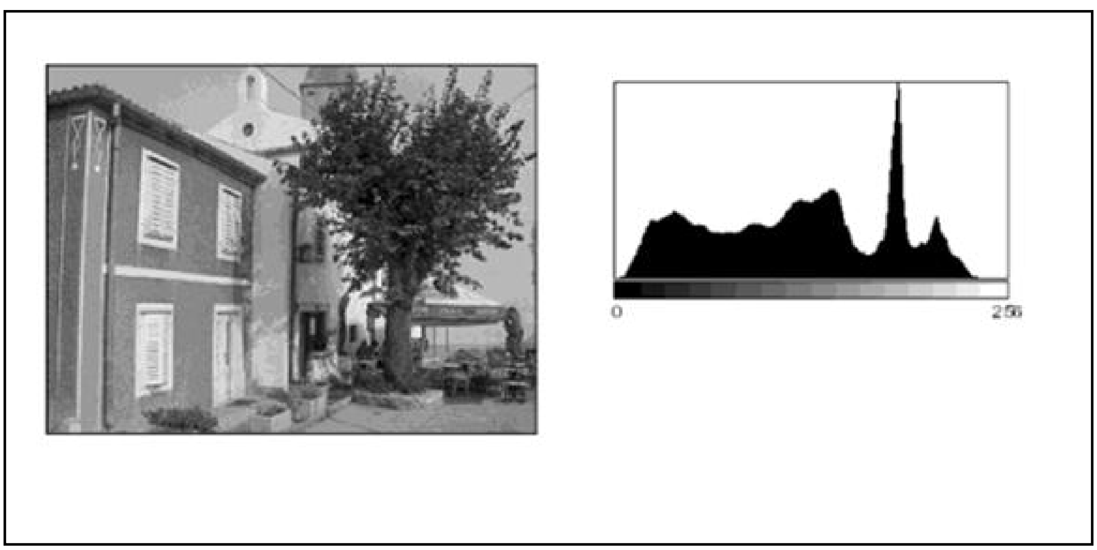


Figure 2.4: An 8 bit gray scale image and its histogram with 256 gray values

As a result h(0) bin indicates the number of all black pixels with 0 as gray value, h(l) bin the number of pixels with 1 as gray value, and so forth. Figure 2.5 provides a histogram example of an image with 16 possible gray values. In this figure, the histogram is illustrated as an array of image's gray level. Each element includes the number of pixels with a specified gray value. The value 2 at index 1 means that the image includes two pixels with one as a gray value.

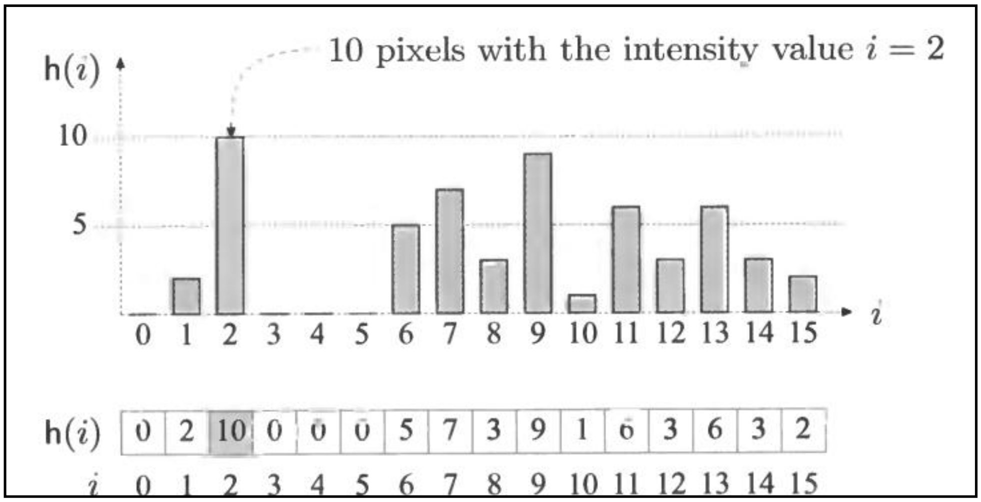


Figure 2.5: Histogram array for an image with 16 possible gray values

2.3.2.1 Histogram Equalization (HE)

The goal of HE is to modify the histogram in order to acquire a uniform histogram for the enhanced image. In this method, lower local contrast areas will gain a higher contrast. It is a global enhancement technique; the image is enhanced uniformly. On the other hand, an interesting image feature might require local enhancement for better visual appearance.

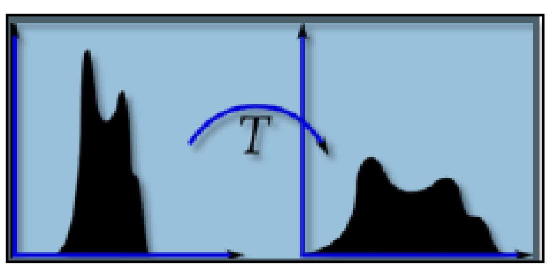
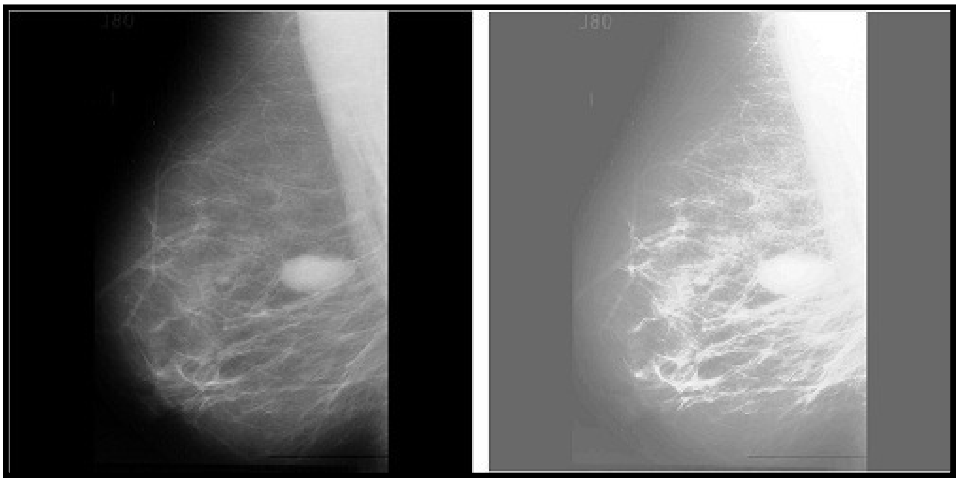


Figure 2.6: Histogram Equalization



(a) **(b)**

Figure 2.7: (a) Original Image (b) Histogram Equalized Image

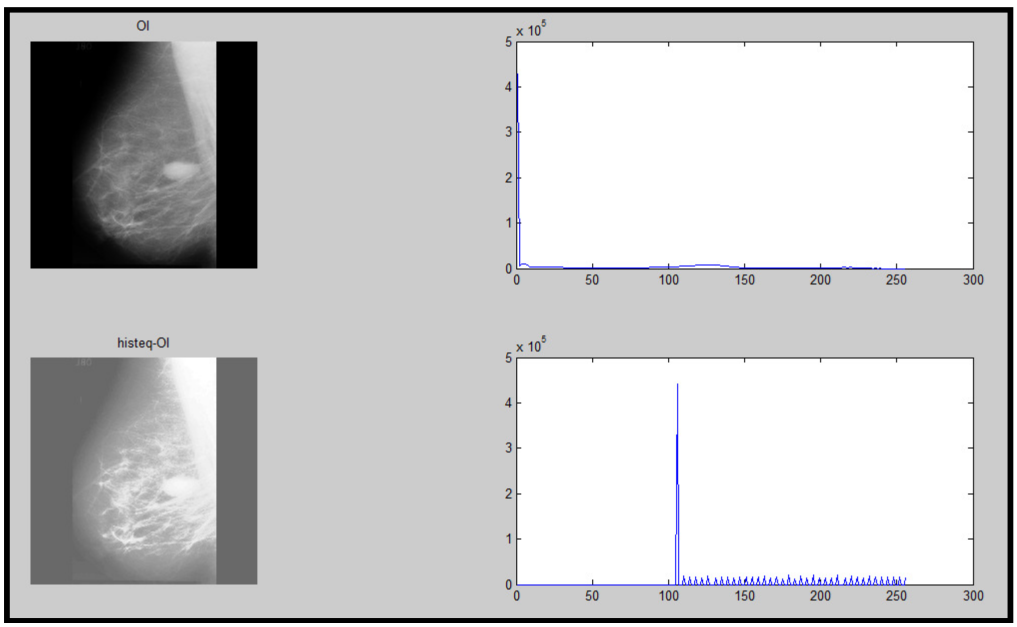
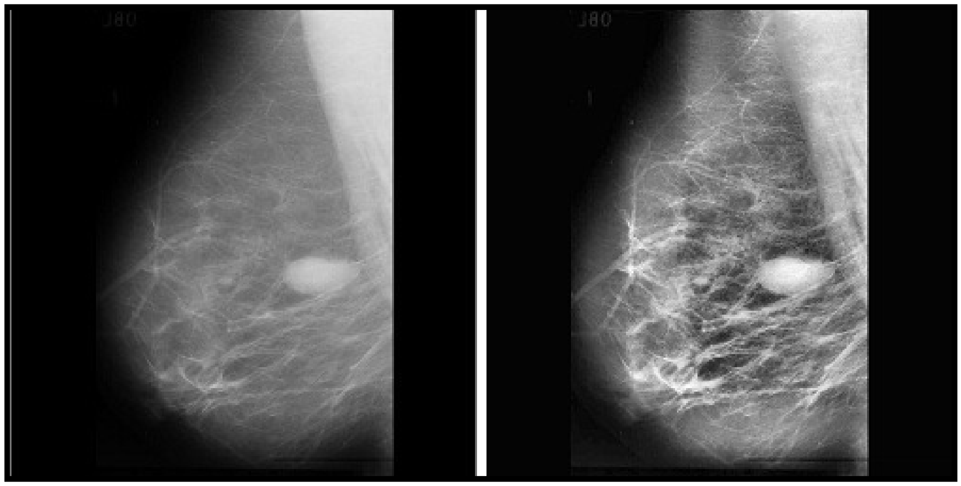


Figure 2.8: Histogram of Original and Histogram Equalized Image

2.3.2.2 Adaptive Histogram Equalization (AHE)

AHE is an enhanced version of the HE; it is based on local window processing. In this method, the intensity of each pixel is mapped to a value determined by calculating the histogram of a window centered at that pixel. This window contains pixels in the surrounding area of a specified pixel (called its contextual region). Nevertheless, AHE provides a strong enhancement which leads to noise amplification.



(a) **(b)**

Figure 2.9: (a) Original Image (b) Adaptive Histogram Equalized Image

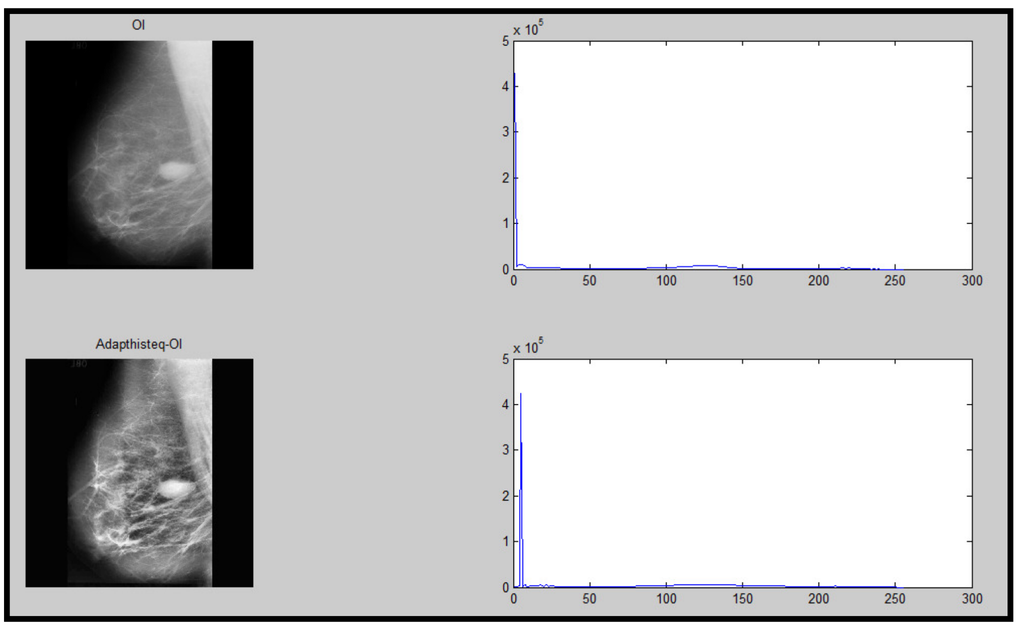


Figure 2.10: Histogram of Original and Histogram Equalized Image

2.3.3 Logarithmic Transform

The log transformation is given by the expression,

$$s = c\ log(1 + r)$$

where c is a constant and it is assumed that $r \geq 0$.

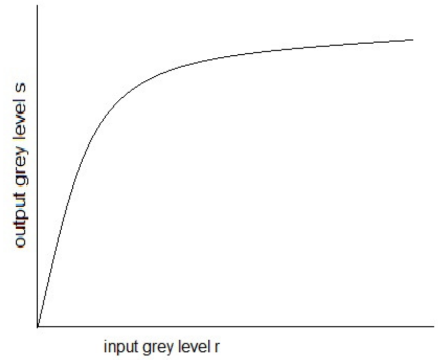
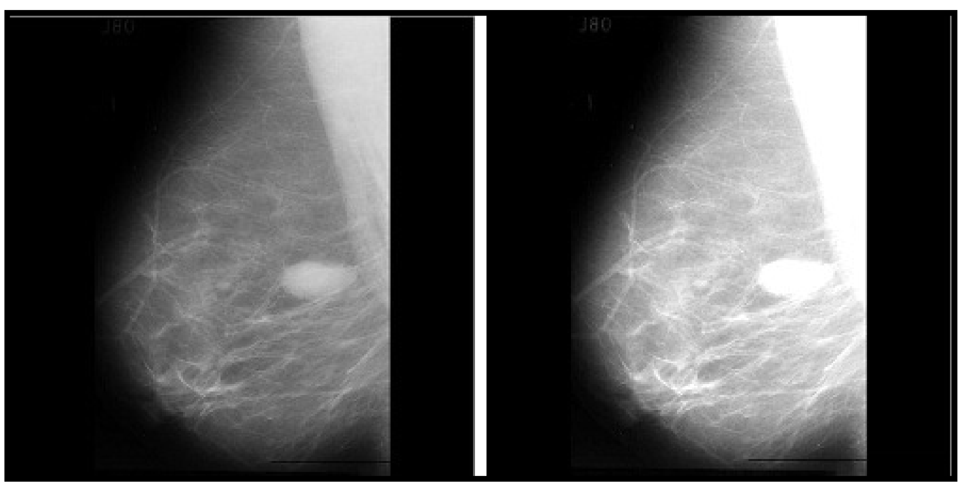


Figure 2.11: Logarithmic Transformation

The shape of the log curve in fig. A tells that this transformation maps a narrow range of low-level grey scale intensities into a wider range of output values. And similarly maps the wide range of high-level grey scale intensities into a narrow range of high level output values.



(a) **(b)**

Figure 2.12: (a) Original Image (b) Logarithmic Transformation

2.3.4 Morphological Processing

Morphological image processing methods are effective for extracting components of image that are useful in describing and representing region shapes. This section provides an overview of the most important morphological operators.

2.3.4.1 Structuring Element (SE)

A SE is a shape that interacts with the original image to investigate how this shape misses or hits the shapes in the given image. It is a typical element in morphological operations such as erosion and dilation. A SE can be defined as functions of real-valued 2D:

$$\mathrm{H}(\mathrm{i},\mathrm{j}) \in \mathbb{R}, \qquad \forall(\mathrm{i},\mathrm{j}) \in \mathbb{Z}^2$$

2.3.4.2 Dilation and Erosion

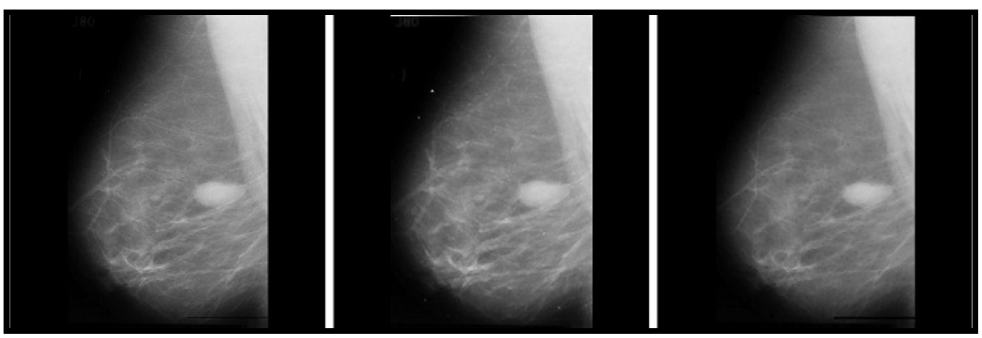
Dilation and Erosion are two fundamental morphological operators since all other operators depend on their combinations.

Dilation is the operation that "thickens" or "grows" object boundary in an image. It is defined by adding the maximum values of the SE to the current sub-image values:

$$(I \oplus H)(u,v) = \max_{(i,j)\in H} \{I(u+i, v+j) + H(i,j)\}$$

Erosion is the operation that "thins" or "shrinks" object boundary in an image. It is defined as the minimum of differences:

$$(I \ominus H)(u,v) = \min_{(i,j)\in H} \{I(u+i, v+j) - H(i,j)\}$$



(a) (b) (c)

Figure 2.13: (a) Original image (b) Dilated image (c) Eroded image

Figure 2.13 shows an image and the result of dilating and eroding this image. As shown in this figure, dilated image is brighter than the original and in which dark and small details have been eliminated or reduced. In contrast, eroded image has the opposite effect of the dilated image.

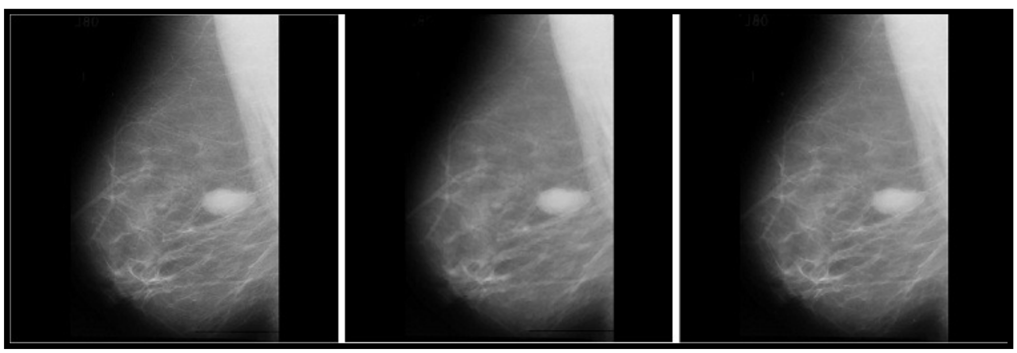
2.3.4.3 Opening and Closing

The two most significant operations that combine dilation and erosion operators are closing and opening.

Opening is accomplished by performing erosion operation followed by dilation operation with the same SE. This can be defined as:

$$I \circ H = (I \ominus H) \oplus H$$

Closing eliminates dark details from the image while keeping bright features relatively unmodified.



(a) (b) (c)

Figure 2.14: (a) Original image (b) Opened Image (c) Closed Image

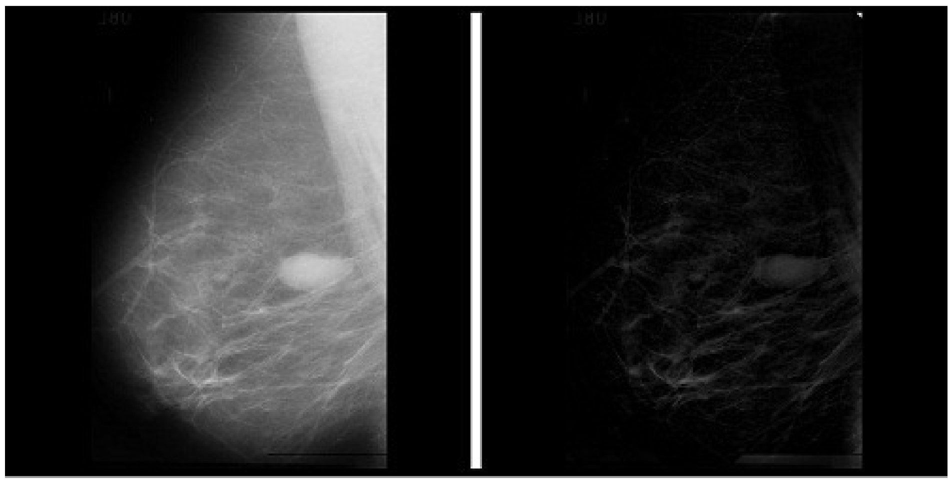
Figure 2.14 shows an image and the result of opening and closing operation. As shown in this figure, the result of opening operation is an image with size decreasing of bright and small details without affecting the darker gray levels. On the contrary, closing the image decreases the sizes of the dark and small features with small effect on the bright details.

Opening in gray scale eliminates small light details but it does not change the overall gray levels and large bright features.

2.3.4.4 Top hat transformation

It is a morphological filter that subtracts an opened image from the original. Top hat transform is used to extract the small elements and detail form a given image by suppressing the background and highlighting the foreground objects. Top hat transformation can be defined as:

$$h = I - (I \circ H)$$



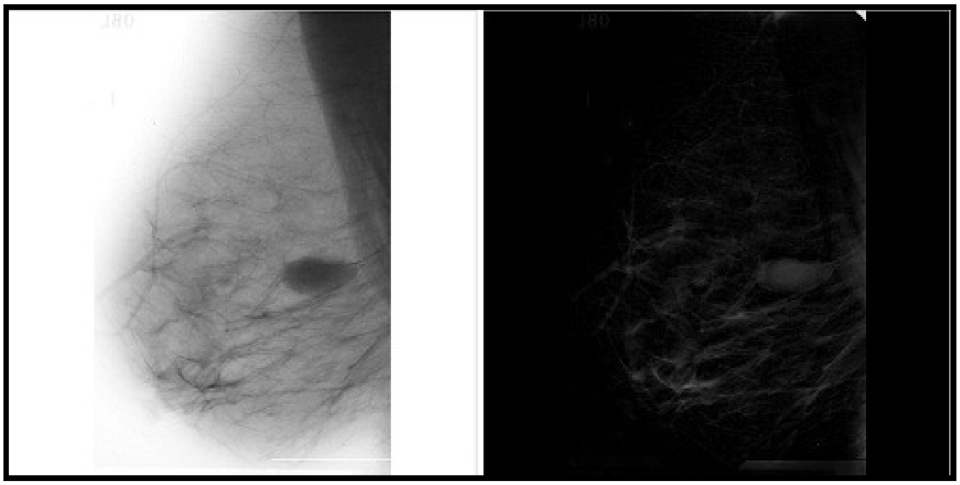
(a) (b)

Figure 2.15: (a) Original Image (b) Top hat Transformation

2.3.4.5 Bottom hat transformation

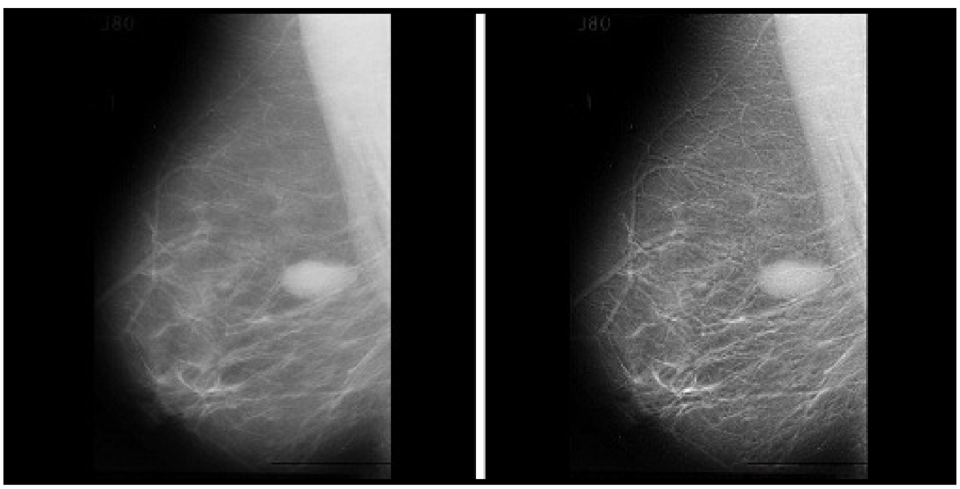
It is a morphological filter that subtracts a closed image from the original. This transformation may be used when the image is the complement to suppress the background objects and highlight the foreground objects. Bottom hat transformation can be defined as:

$$b = I - (I \cdot H)$$



(a) **(b)**

Figure 2.16: (a) Original Image (b) Bottom hat Transformation



(a) **(b)**

Figure 2.17: (a) Original Image (b) Top and Bottom hat Transformation

In Figure 2.17, Both top-hat and bottom-hat filters have been used and the result have been combined afterwards by adding the image to fit the result of the top-hat filter and then subtracting the result from bottom hat filter for better enhancement.

2.3.5 Multi-scale (Multi-resolution) Processing

Digital images generally contain connected areas of similar gray level and texture that form objects. Objects with small size or low in contrast are studied at high resolutions while a coarse view is needed to examine an object with large size or high in contrast. If low and high contrast objects or small and large objects are present all together, it can be advantageous to examine them at a number of resolutions [11]. This is the primary motivation of multi-resolution processing. Multiresolution framework allows decomposing an image into different resolution levels where objects are separated according to their sizes and resolution.

2.3.5.1 Image Pyramid

An image pyramid is a set of images with decreasing resolution assembled in pyramid shape. Figure 2.18 shows an image pyramid for representing an image. The base (at level J) of the pyramid contains a representation with high resolution while the apex (at level 0) holds an approximation with low resolution. In addition, Figure 2.18 demonstrates that both the resolution and size decreases as moving up the pyramid

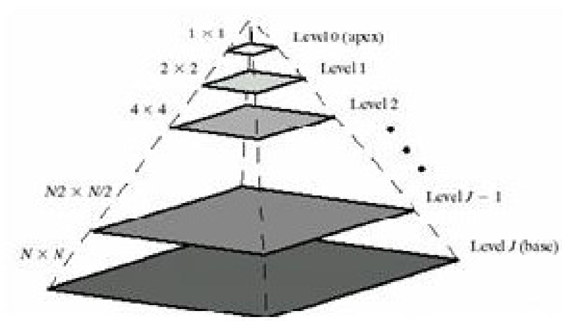


Figure 2.18: Image Pyramid [11].

A simple system for building pyramids of an image is shown in Figure 2.19. This system creates two types of pyramid for an image [11]:

- Approximation pyramid: It holds one or more approximations for the original image.
- Prediction pyramid: It holds the required information for constructing the approximations with higher resolution at the other levels.

These two pyramids with levels as an example are built by repeating the processes in the block diagram of Figure 2.19 in times. In the first iteration, the original image is used as the level input image. Each iteration consists of three steps which are performed as follows:

1. Compute level approximation with reduced resolution. This is performed by applying an approximation filter and then down-sampling the filtered result by a factor of 2 [11].

2. The output of Step 1 is up-sampled by a factor of 2 and then the result is required to be filtered using interpolation filter to produce a prediction image [11].

3. Estimate the difference between the input of Step1 and the output of Step2. This result will be the prediction residual pyramid at level [11].

In the consequent iterations, the approximation result of the previous pass is applied as an input to the next pass.

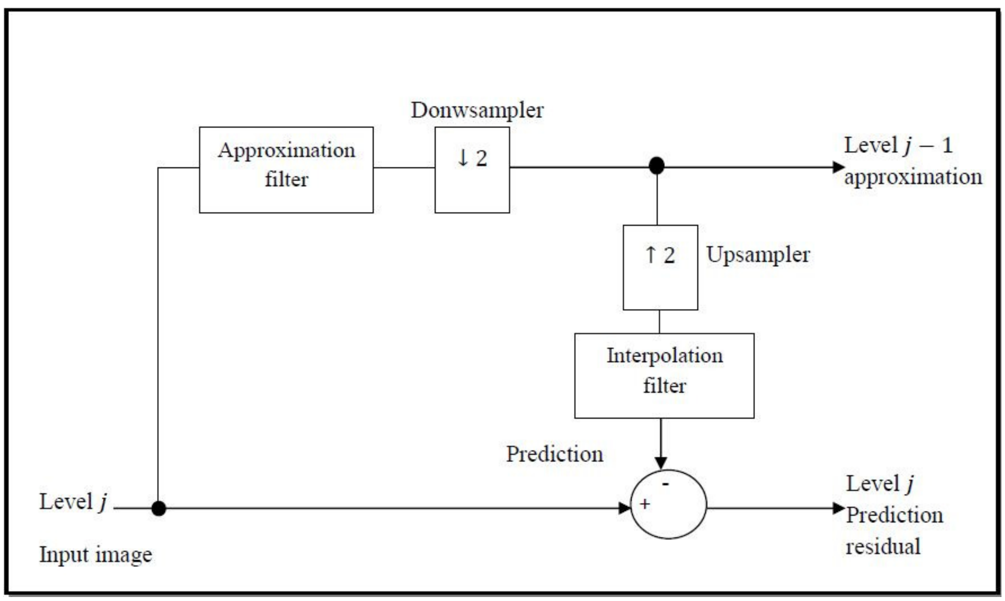


Figure 2.19: Block diagram for creating image pyramid [11].

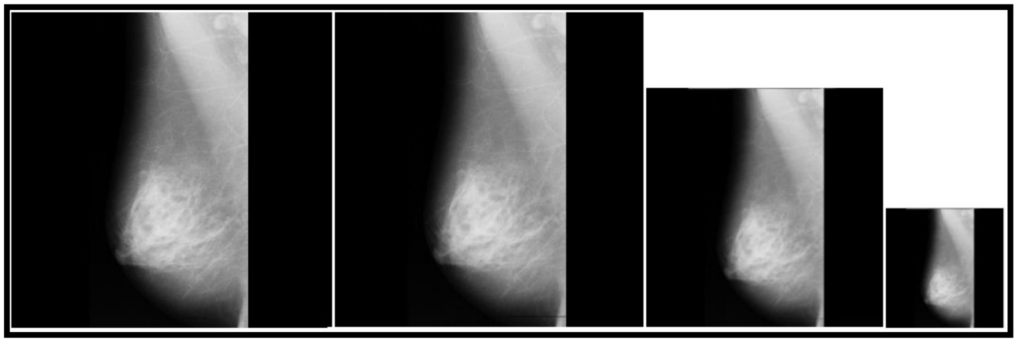


Figure 2.20: Reduction using Image Pyramids

2.3.5.2 Laplacian Pyramids (LP)

The LP is an example of image pyramid which captures the data using image pyramid where each scale includes a reduced-resolution approximation. At each scale LP produces two images: coarse approximation image and band-pass image (fine layer). The coarse approximation is acquired by down-sampling (reducing the image size by half). Then, the band-pass image is obtained by up-sampling the coarse layer, and taking the difference with the original as shown in Figure 2.21. This procedure is iterated using the coarse version. On the other hand, Figure 2.22 expresses the reconstruction of the original image from the LP. In reconstruction phase, the process starts by up-sampling the coarse layer and adds the result with band-pass image to get the original image.

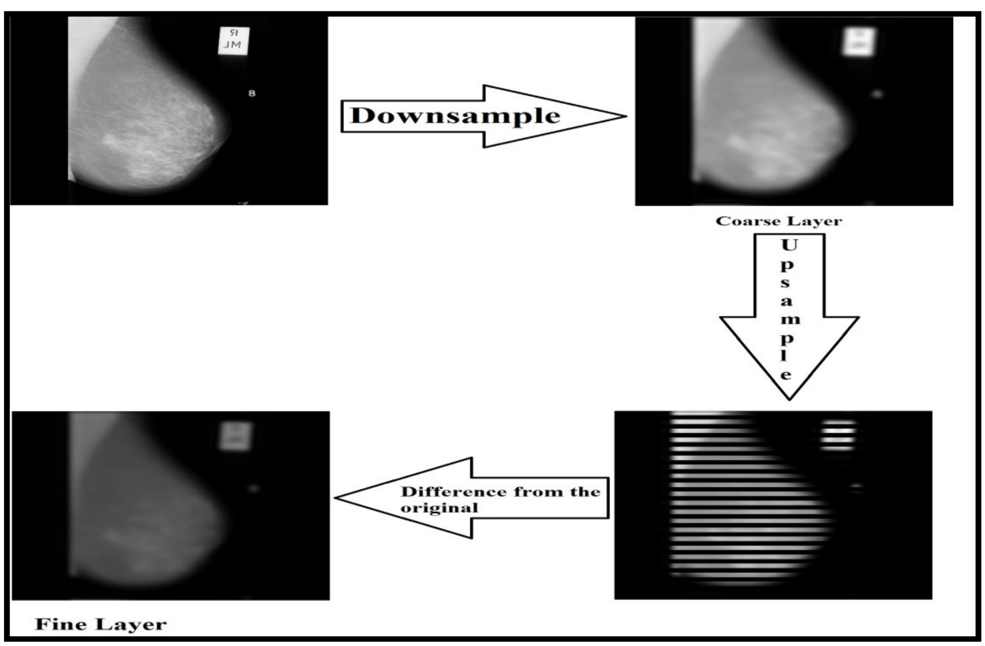


Figure 2.21: Block diagram for creating LP (one level)

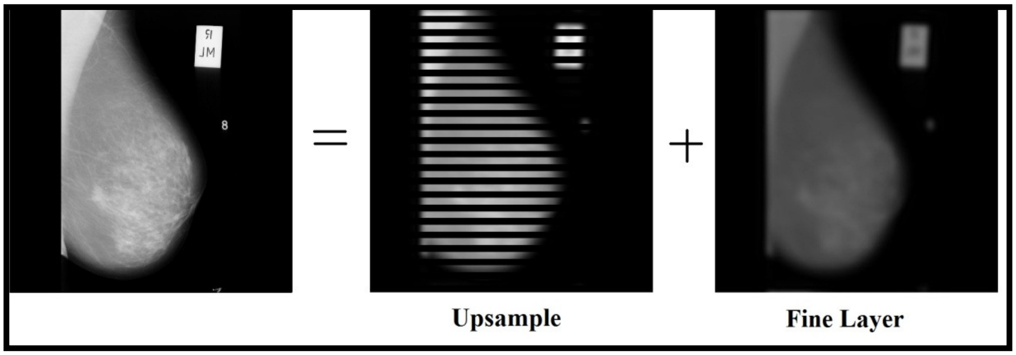


Figure 2.22: Block diagram for reconstructing image using LP (one level) .

2.3.5.3 Wavelet Transform (WT)

In multi-resolution imaging techniques described above, a series of image approximations is created by a scaling function. This scaling function builds an approximation from an adjacent approximation in the pyramid by reducing its size by a factor of two. On the other hand, WT is an expanded version of multi-resolution approach where wavelets are used to capture the information's difference between adjacent approximations [11]. This section gives an overview of some basic WT methods

A. **Filter banks**

Filter banks are the essential components in applying the WT. Generally, two types of filters are required in WT [16].

- **Analysis filter banks:** take an input signal and decomposes into two components. Figure 2.23 (a) shows a general scheme for analysis filter bank with two filters: high-pass filter H_1 and low-pass filter H_0. As shown in the figure, the input *x(n)* is passed through two paths [16]:
    - First path process the input with H_0 and then downsample the result by a factor of 2.
    - Second path process the input with H_1 and then downsample the result by a factor of 2.
- **Synthesis filter bank:** reconstruct the signal from its components. Figure 2.23 (b) illustrates the building blocks of the synthesizing process with two filters: high-pass filter G_1 and low-pass filter G_0. The input $y_0(n)$ is

upsampled and then filtered by G_0 whereas $y_1(n)$ is upsampled and then filtered by G_1[16].

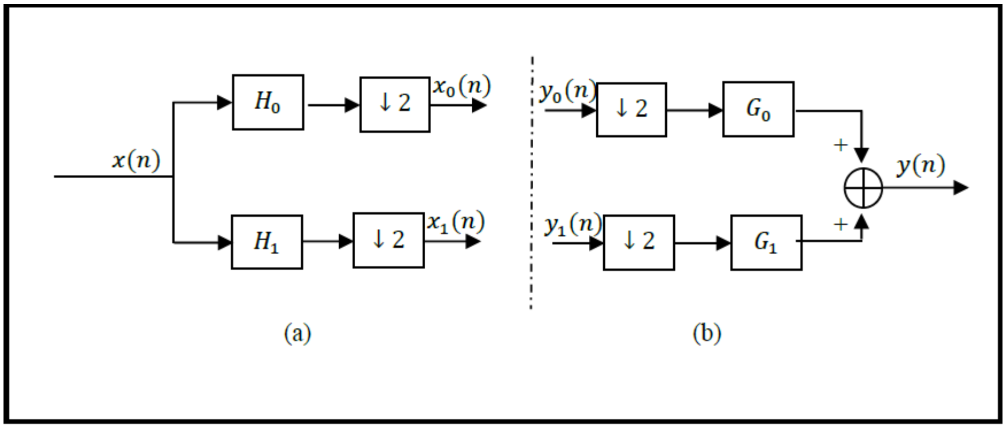


Figure 2.23: Filter Banks; (a) Analysis filter bank, with H_0 as lowpass filter and H_1 as highpass filter (b) Synthesis filter bank with G_0 as lowpass filter and G_1 as highpass filter [16]

B. Discrete Wavelet Transform (DWT)

The decomposition of an image using DWT splits the image of size N×M into a number of scales where each scale *j* contains four sub-bands (sub-images) of size $(\frac{N}{2^j} \times \frac{M}{2^j})$, namely the LL(low low), LH (low high), HL (high low), and HH (high high) sub-bands. The LL sub-band at each scale consists of low frequency components and is further divided at higher level of decomposition. LH, HL and HH sub-bands at each scale contain high frequency detail. The HL sub-band includes the horizontal structures while the LH sub-band gives the vertical features. The HH sub-band represents the diagonal detail of the image [16].

Figure 2.24 shows the block diagram for an image decomposition using DWT into one scale. This decomposition is performed by applying the filtering operation along image's rows and then along columns. The output of these filters is four sub-bands of size $(\frac{N}{2^j} \times \frac{M}{2^j})$. Figure 2.25 shows the result of applying DWT to decompose a gray scale image into four sub-bands.

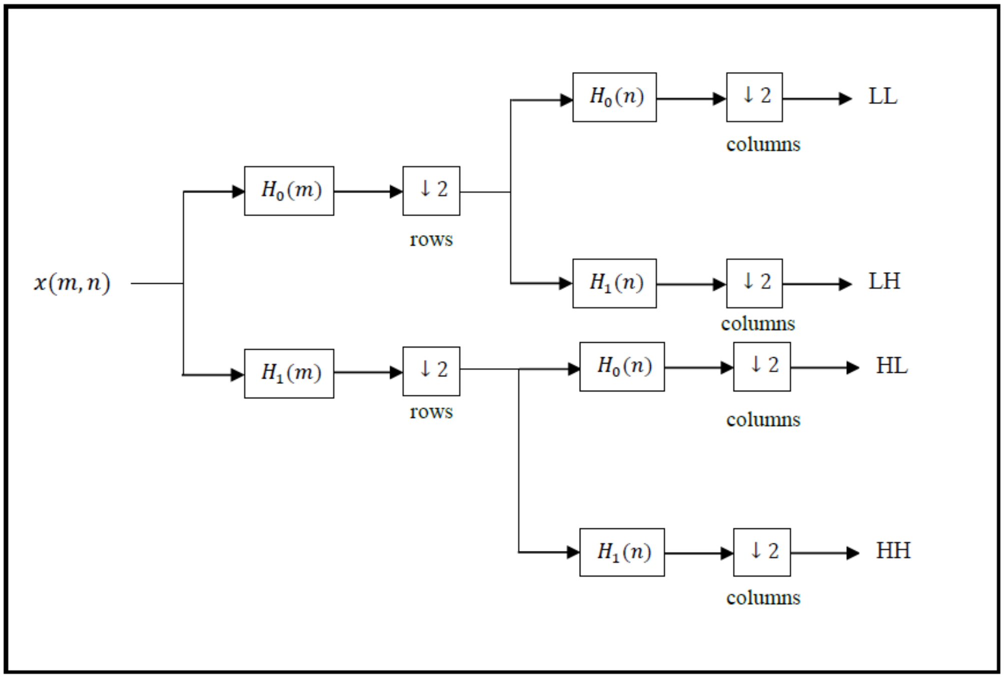


Figure 2.24: Decomposition of image into one scale using DWT; H_0: low-pass filter and H_1: high-pass filter [16]

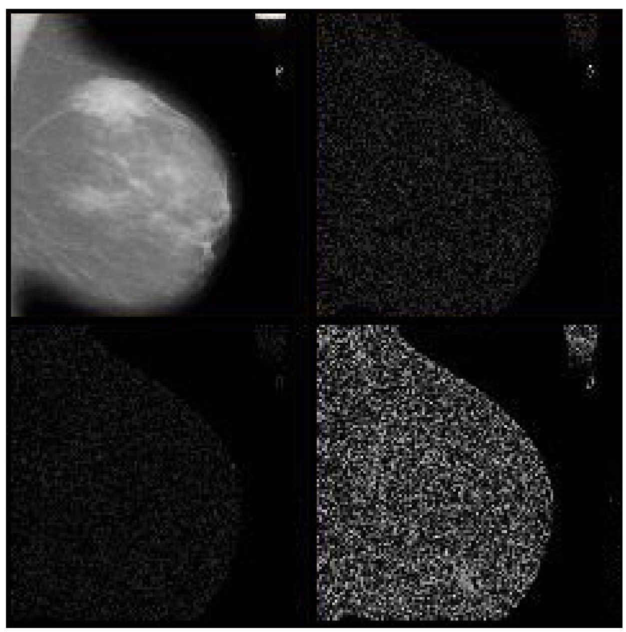


Figure 2.25: Decomposition of a mammogram into 4 sub-bands with one scale

Decomposition of image into a number of scales is performed by recursively applying the scheme of Figure 2.23 to the LL sub-band. Coarser version (LL) of the image and the new three details sub-images are produced in each phase of this recursion. Figure 2.26 shows a block diagram for producing two scales of an image using the recursive scheme.

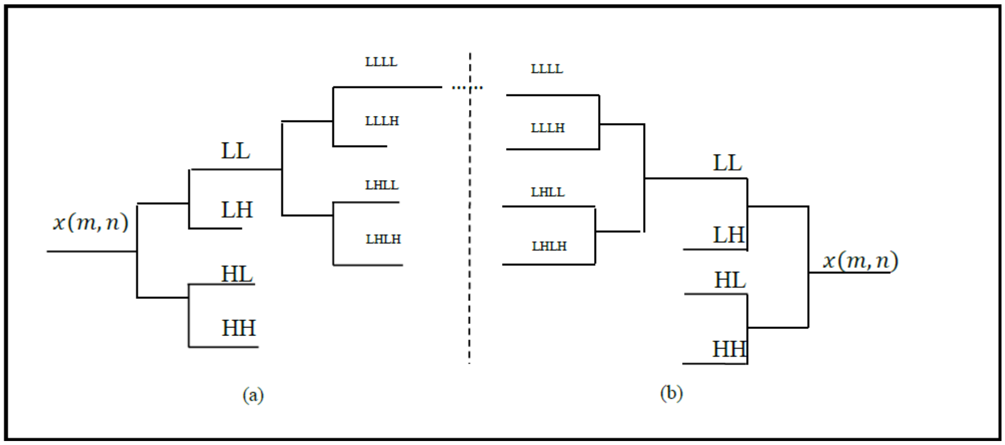


Figure 2.26: Two scales of DWT; (a) wavelet decomposition using iterated filter bank; (b) reconstruction of image from its coefficients[16]

C. **Dyadic Wavelet Transform (DyWT)**

DWT is not a shift invariant, which means that a shift in the original image leads to produce a different image. DyWT overcomes this limitation by keeping the size of each sub-band as the size of the original image.

A mother wavelet is first chosen and then dilated by powers of two. The mother wavelet along with its dyadic dilates are convolved against the original function to produce a sequence of functions termed the *dyadic wavelet transform*.

DyWT also splits an image of size MxN into a number of scales where each scale consists of four sub-bands (LL, LH, HL, HH) each of size MxN. DyWT differs from the DWT in the size of sub-bands; in case of DyWT the size of each sub-band is the same as the original image size because there is no up-sampling / dow-nsampling operations. The decomposition of image into two scales is showed in Figure 2.27.

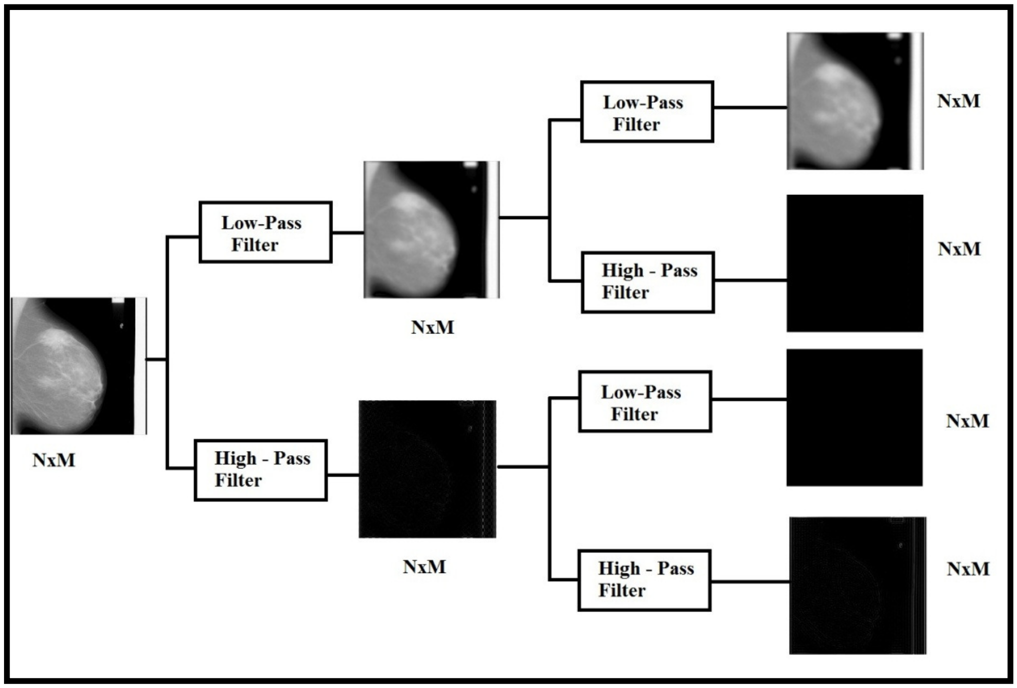


Figure 2.27: One Scale DyWT

D. Contourlet Transform (CT)

DWT and DyWT capture the directionality information in an image using only three directions (horizontal, vertical, and diagonal). However, this is not effective for capturing the directional features in an image with smooth contours in different directions. CT overcomes this limitation by adopting the use of directional filter banks (DFBs).

CT is a multi-scale method that includes multi-directional decomposition. In CT, multi-scale decomposition is performed by LP while the directional decomposition is performed by the directional filter-banks (DFBs) [17]. Figure 2.28 presents a CT as an arrangement of LP decomposition and a DFB. First, LP decomposition is applied and then band pass approximation (*d*) became an input into a DFB. This approach iterates on the coarse image (*c*).

Figure 2.27: Block diagram of CT; c is the coarse approximation; d is the difference image

- **LP decomposition:**

As explained above, LP produces two images at each scale:

1. *c* (coarse approximation) of the image obtained by lowpass filtering and downsampling.

2. *d* (band pass image) which is the difference between the filtered prediction of the image and original image.

- **DFBs decomposition**

DFBs are intended to capture image content with high frequency such as directional edges and smooth contours. DFBs spilt the image into levels which leads to have 2^k sub-bands. Figure 2.28 shows multichannel view of a 2 levels DFBs to produce $2^k = 4$sub-bands.

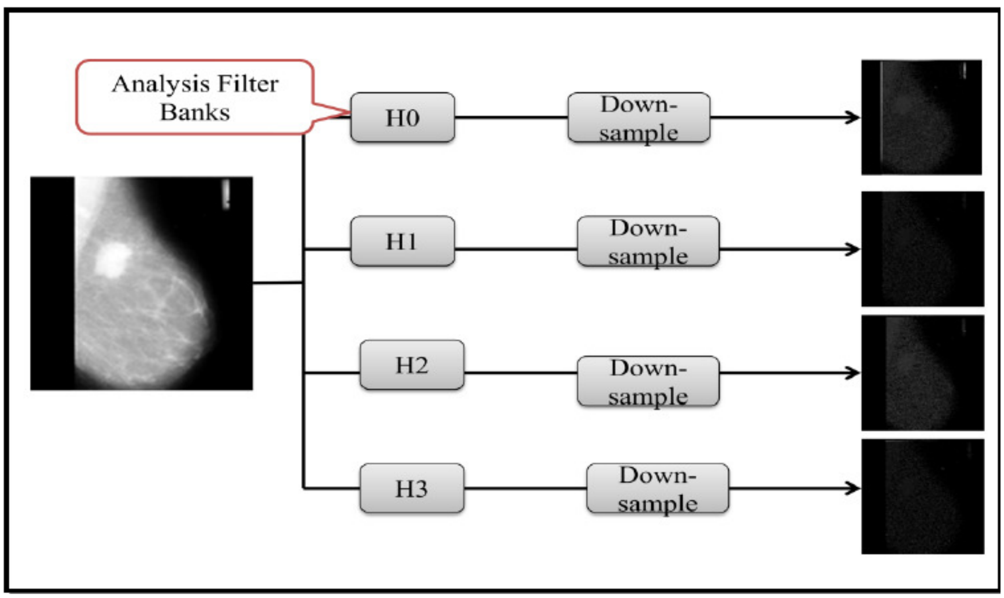


Figure 2.28: Multichannel view of DFBs with k=2 levels($2^2 = 4$)

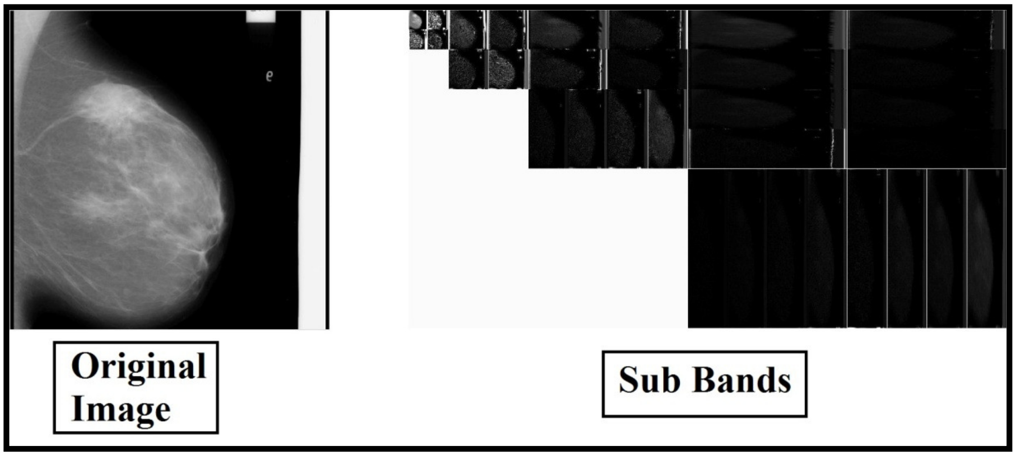


Figure 2.29: CT on a mammogram image into four scales with directional decompositions at scale 1,2,3 and 4 respectively.

2.4 Fuzzy Image Processing (FIP)

FIP is based on incorporating the use of fuzzy techniques in image processing applications. FIP can be defined as the processing of images, their features and segments as fuzzy sets [11].

2.4.1. Fuzzy set theories

The fuzzy set theory is based on determining the measure of membership of an element in a set by giving a value that indicates the level to which the element belongs to the set. The membership value is between 0 (no membership) and 1 (full membership) [11].

2.4.2. Image as a fuzzy set

An image I of size $M \times N$ with L gray levels can be defined as fuzzy set with indication of the membership value for each pixel according to a predefined property (e.g., noisiness, brightness, edginess, etc.). Defining the membership values will be based on the specific application requirements [11].

2.4.3. Image fuzzification

Image fuzzification produces appropriate membership values for an image which causes to transform an image from gray level plane to the membership plane.

FIP has three steps: starting with image fuzzification, modification of membership values, and image defuzzification (see Figure 2.25). Membership values are modified using appropriate fuzzy approach. This modification can be simple modification, classification, or processing by some type of if-then rules [11].

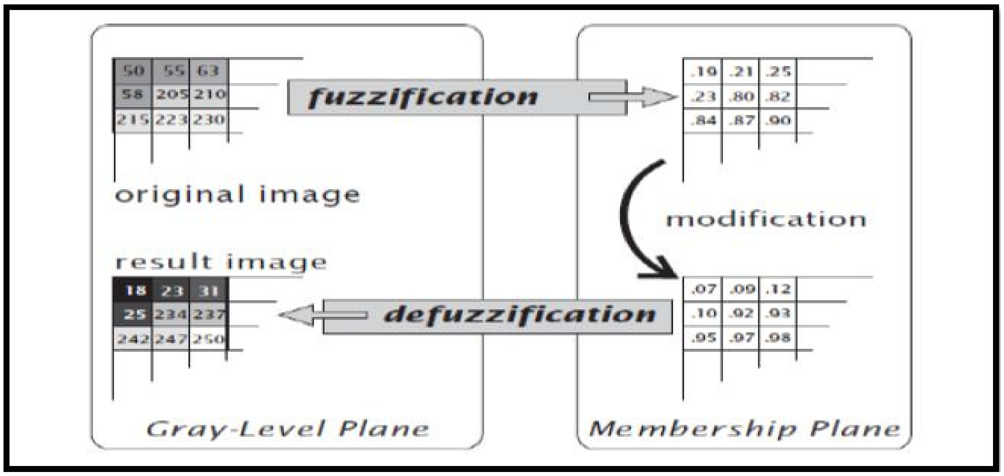


Figure 2.30: Example for FIP [11].

Chapter 3

ENHANCEMENT OF MAMMOGRAM IMAGES

One of the most reliable techniques for early detection of breast cancer is mammography. Nevertheless, the mammogram is a low contrast image which can cause difficulties in distinguishing between the malignant and normal tissues. It motivated the research on contrast enhancement of mammogram images in order to improve the diagnosis rate [8]. Generally, mammogram enhancement contains contrast and intensity modifications, and the reduction of noise, filtering, or edge sharpening. It aims to make the edges or boundaries of the region of interest (ROIs) much sharper, or to enhance the contrast between ROIs and the background [4]. This chapter will focus on a survey of the recent enhancement techniques.

3.1. Enhancement of microcalcification

Various methods have been proposed for the enhancement of mammogram images to highlight microcalcifications. These methods can be separated into two categories: conventional enhancement and feature-based enhancement [4].

3.1.1. Conventional enhancement techniques

The main idea of the conventional enhancement method is to adapt the overall contrast to the local or global features inside a fixed area (neighborhood), and then to change the images using global properties. This technique can be considered as either the global or fixed neighborhood method [4]. In addition, the major techniques used under this category are unsharp masking, histogram equalization, and spatial filtering. Spatial filtering is an operation that changes pixel intensities based on its local neighborhood.

Some recent proposed approaches in the literature adapt more than one technique for the enhancement of microcalcifications. Bouyahia et al. [20] designed a pre-processing step to enhance the quality of mammograms and make the lesions more visible. The proposed technique is a combination of three methods: contrast stretching, unsharp masking filtering, and morphological operations. The first applied method is the unsharp masking filtering to produce a sharper image by amplifying the high-frequency details. After this, contrast stretching is applied to enhance the visibility of the microcalcifications in the mammograms, which enhances the mammogram by stretching the range of intensity values it contains to make full use of the entire range, from 0 to 255. Finally, the morphological operation is employed to enhance mammograms using two operations: top-hat transform and bottom-hat transform. Then, the original image is added to its top-hat and the result is subtracted from the bottom-hat in order to obtain more visible microcalcifications. The results show that the contrast is greatly increased by combining these image enhancement techniques.

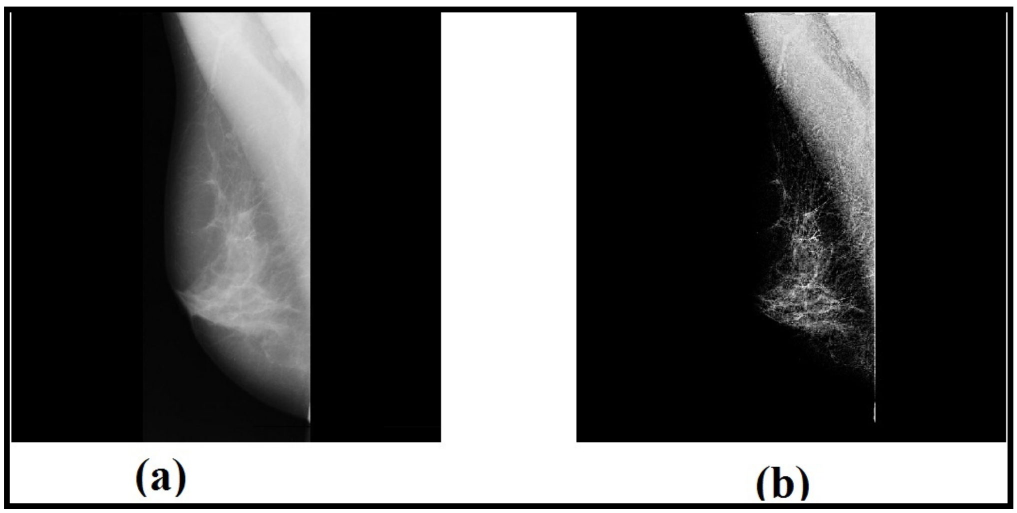


Figure 3.1: Enhanced Image by Bouyahia's method:

(a) Original Mammogram (b) Enhanced Image

3.1.2. Feature-based enhancement

A feature-based enhancement is used to enhance microcalcifications adapted to their features. This section provides a survey of the recent methods based on feature enhancement.

3.1.2.1. Multi-scale approaches

Multi-scale analysis approaches have been used for mammogram enhancement. The commonly used methods are based on wavelet transformation and involve three stages. In the first stage, the mammogram image is decomposed into wavelet coefficients using wavelet transform. Then wavelet coefficients are modified at one or more levels through a global or local operator. Finally, the image is reconstructed from the modified coefficients to obtain the enhanced mammogram.

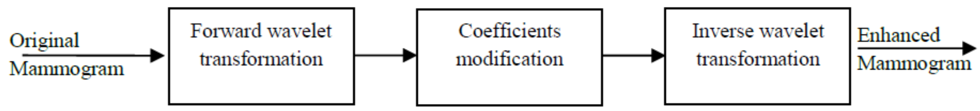


Figure 3.2: Block diagram for wavel et t ransformation forwavelet transformation

A number of multi-resolution representations, including discrete wavelet transform, dyadic wavelet transform, contourlet transform and Laplacian Pyramid decomposition, were investigated to perform mammographic feature analysis. The survey of these methods is presented below.

A. Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) has been investigated in several techniques for the enhancement of mammograms [8, 9, 21]. The major difference between these techniques is the proposed way for modifying the coefficients. Tang et al. [8] proposed the use of a multi-scale local contrast measure to modify the coefficients. Initially they decompose the image into k scales. All the sub-bands at kth scale are enhanced using a uniform contrast enhancement factor and the low resolution sub-band at (k-1) scale is reconstructed. Using the reconstructed low resolution sub-band and enhancement parameter, high resolution sub-bands are enhanced at (k-1)th scale. This process continues until the enhanced image is obtained. In this method, the wavelet coefficients at different scales are uniformly enhanced because the same manipulation factor is used.

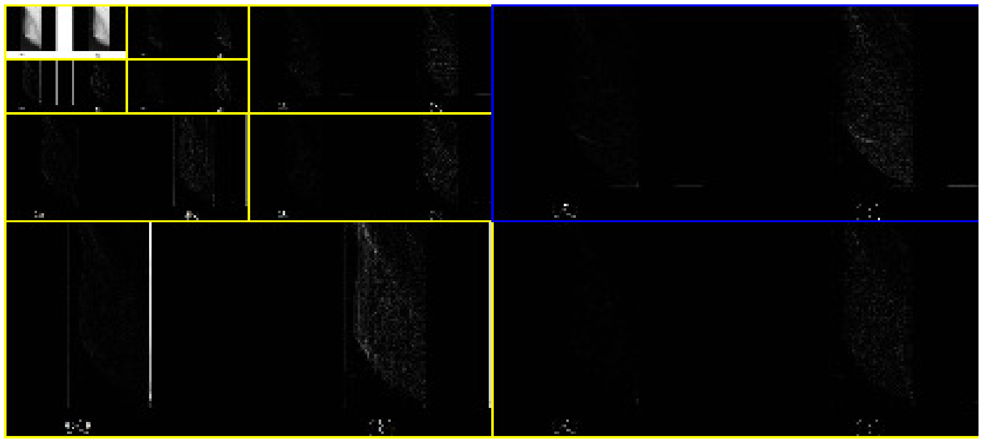
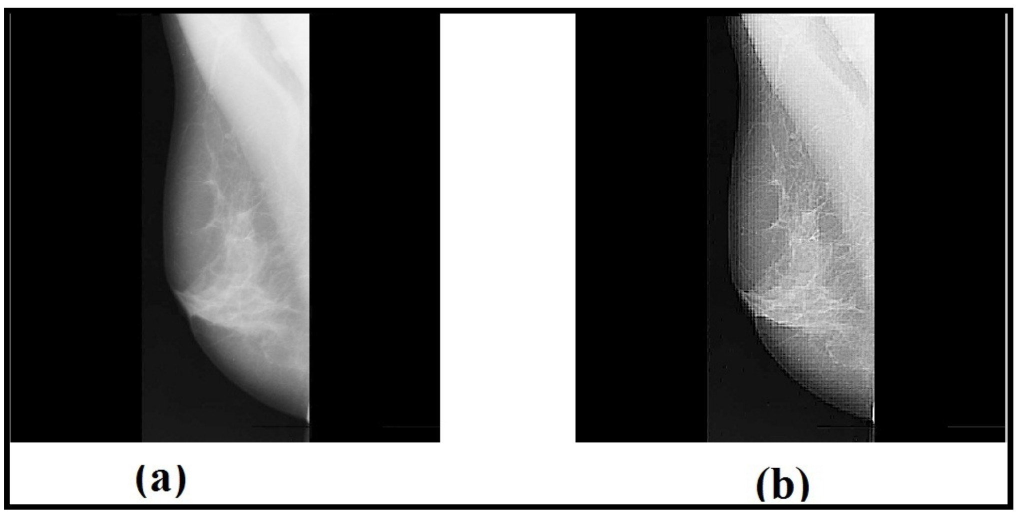


Figure 3.3: Sub-band decomposition using DWT



3.4: Enhancement by Tang method

DWT is not a translation invariant, which means that a shift in the original image leads to produce a different image; and this is considered the main drawback of applying DWT.

B. Contourlet Transform

Contourlet transform (CT) is a multi-scale method that involves multi-directional decomposition. In CT, first an image is decomposed using Laplacian Pyramid and then directional filtering is applied on each sub-band. CT deals with singularities such as edges in a powerful manner and is much more robust than the DWT. The DWT has basis functions in only three directions, whereas CT has basis functions at various orientations [9]. CT has been explored in various techniques for mammogram enhancement. Lizacano et al. [22] developed a method based on the CT that consists of two stages. In the first stage, histogram equalization is applied to improve image's contrast. After that, the contourlet transform is used and then the contourlet coefficients above a threshold are retained. This threshold is based on estimation of the variance of the input image.

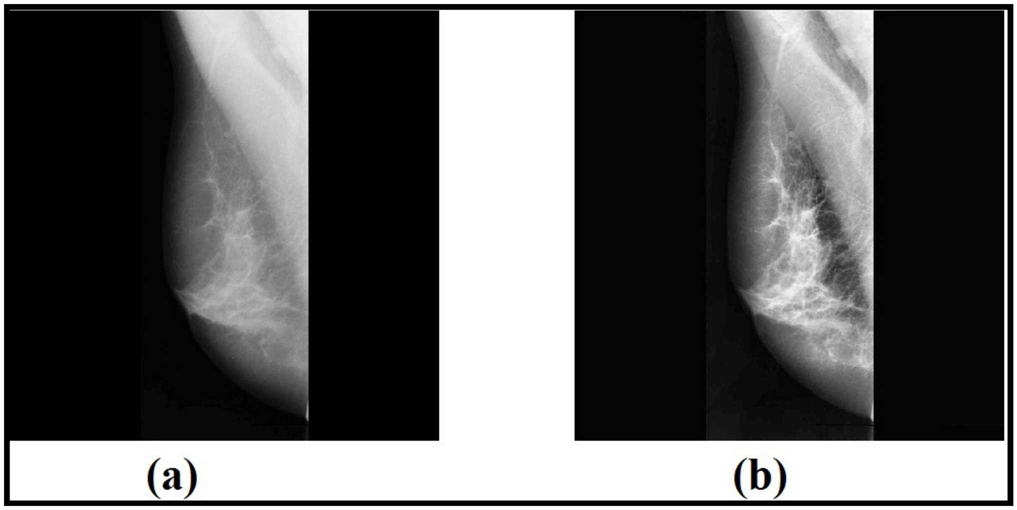


Figure 3.5 :Enhancement by Lizacano et al. [22]

Contourlet transform is not shift invariant. To overcome these issues Nonsubsampled Contourlet Transform (NSCT) was developed where the redundancy is not a major issue [9] NSCT is a multi-scale, multidirectional, and fully shift invariant transform. NSCT is implemented by using Nonsubsampled Pyramid decomposition followed by Nonsubsampled Directional Filtering. Munoz et al. [9] presented a method based on NSCT to enhance the contrast of mammogram images. The enhancement operation is performed by multiplying the sub-band with an empirical weight that is calculated as the sub-band standard deviation multiplied by three.

C. Dyadic Wavelet Transform

Dyadic wavelet transform is an overcomplete (redundant) multi-scale approach which is known to be shift invariant. Dyadic wavelet transform was employed in different works of mammogram image enhancement, and the focus of these explorations has been to enhance mammogram features while minimizing noise enhancement. However, it is not considered simple to distinguish the features of the image from the noise and, therefore, requires balancing between the denoising and the enhancement of image in order to retain all significant features.

In wavelet framework, linear and non-linear enhancement operators have been employed. Linear enhancement is based on the use of linear function to modify the wavelet coefficient [23]. On the other hand, nonlinear enhancement is used to minimize the saturation of the coefficients which causes a loss of details after the reconstruction phase [23,24]. However, most of the presented methods are based on a nonlinear enhancement method proposed by Laine et al. [25]. Yet, the difference between these methods is in the way of defining the threshold.

Two methods were explored in the existing techniques of mammogram enhancement based on the undecimated wavelet transform. The first method exploits the use of the threshold in the denoising stage and then enhances the image using the non-linear function [23,24, 26]. On the other hand, the second one measures the relationships between wavelet coefficients in successive levels of the analysis, derives the coefficient from noise, and then uses non-linear mapping functions for the enhancement [27].

o ***First Approach*** **[28]**

This approach consists of two steps: the first one is to use the threshold for denoising and then to perform enhancement using non-linear functions. Mencattini et al. [24] developed an algorithm for enhancing and denoising mammogram images using this approach for the detection of both microcalcifications and masses. In this method, the denoising is performed based on a threshold, where the threshold is computed using information concerning local noise variance. Then, the enhancement is performed at each scale by applying the enhancement operator to the denoised wavelet coefficients and modifying them with a threshold and gain. The threshold is defined using the maximum value of the output coefficients of the filters. The gain is selected based on the scale, as a fixed gain along the scale causes an under-enhancement of the coefficients at a deeper level due to a very high value of coefficients. In [23], the denoising is preformed using a shrinkage operator with the threshold based on local noise variance information. Then, the non-linear mapping function changes the coefficient with threshold and gain. The first threshold is based on the noise estimation while the second threshold is estimated following the approach presented in [23]. In [26], the denoising is carried out using soft threshold, where the threshold is level dependent and is computed as a multiple of the level number and the log of maximum coefficient value.

o **Second Approach**

Scharcanski et al. [27] follow the second approach in their method for image denoising and enhancement which is based on the dyadic wavelet transform with two detail images – horizontal and vertical. At each scale, coefficients associated with noise are supposed to be Gaussian random variables. Whereas, coefficients associated with edges are assumed to be Generalized Laplacian random variables. These probability functions are used to determine a shrinkage function which is applied to inter-scale and intra-scale wavelet coefficients in the denoising process. Then, the coefficients are modified using threshold and gain. This threshold is defined to be the median of the absolute value of the denoised coefficients while the gain is user selected.

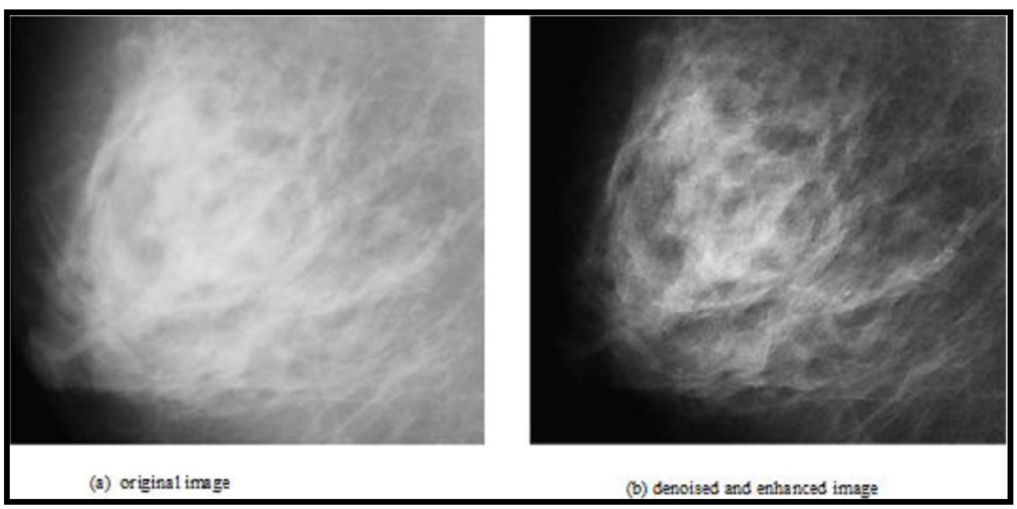


Figure 3.6:Denoised and Enhanced image using the Scharcanski et al. method [27]

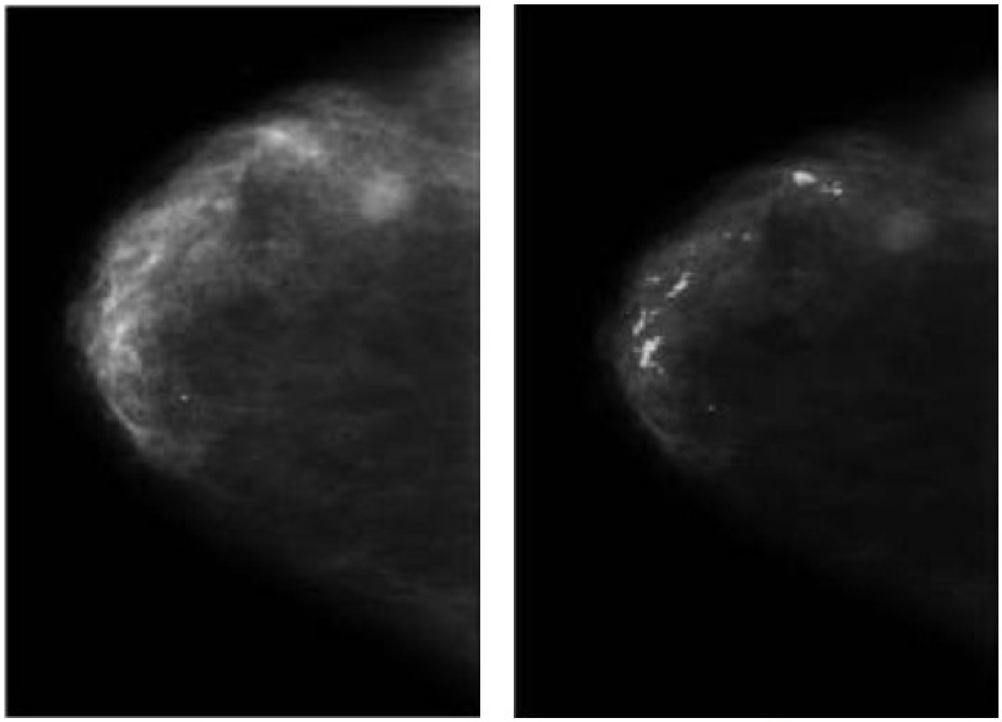
D. Laplacian Pyramid Multi-scale

The Laplacian Pyramid is another multi-scale approach which has been introduced in image compression and has been used for wide image enhancement.

Liu et al. [29] proposed a method for contrast enhancement of mammograms using the Laplacian Pyramid. In the proposed method, the enhancement is performed in the reconstruction step after decomposing the image into a multi-level Laplacian Pyramid. In this method, the used contrast measure is multi-scale and changes the coefficients at all levels by modifying them using the same contrast manipulation factor. However, this method is extended by adding a weight for each level in [30] because the author observed that calcification frequently takes place at certain levels.

3.1.2.2. Fuzzy method

Statistics and fuzzy theories has also been studied to improve microcalcifications contrast. In this approach, the mammograms are converted into a fuzzified version based on the maximum fuzzy entropy principle because the mammograms include some degree of fuzziness. Then, statistics are employed for non-uniformity measures of the regions. Kalra et al. presented an approach for contrast enhancement of the ROI's features which used a fuzzy algorithm with Tsallis entropy. In the proposed technique, the Tsallis Entropy threshold is calculated. Then, the contrast is enhanced based on the non-uniformity factor which is then computed using local information [31; 32].



(a) (b)

Figure 3.6: Enhanced image using the fuzzy method [33].

3.2. Enhancement of masses

Masses enhancement methods can be categorized as: (1) local processing approach; and (2) multi-scale processing approach.

3.2.1. Local Processing Approach

The local processing methods are based on modifying the intensities of pixels. There are a number of such approaches [34, 35]. The method proposed by Riyahi and Younesi [34] is based on the linear transformation of intensities by multiplying each pixel's intensity with a constant empirical value. Wang et al. [35] proposed an algorithm to enhance the mammogram using exponential transformation. The aim of this method is to compress low level intensities while enlarging the intensities of bright pixels, and is based on the concept that the masses occupy relatively high intensities. Kom et al. [7] modified the local contrast of each pixel using the logarithmic function. In this approach, a limit between bright regions and dark region is selected according to the intensities values of the image. Then, if the pixel value is smaller than the selected limit, the value will be modified using the logarithmic function; otherwise, the intensity value will be changed by the inverse of the function (exponential function). Thus, the logarithmic function enhances the dark areas (lower gray level) while the exponential function (inverse of the logarithmic function) enhances the bright areas (higher gray levels).

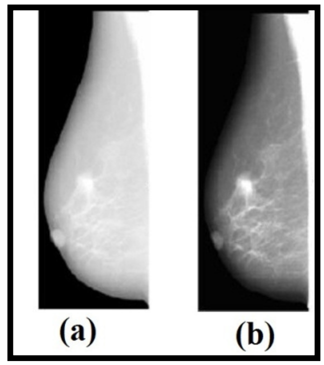


Figure 3.7: Enhancement by Wang method: (A) original image; (B) enhanced image

3.2.2. Multi-scale Processing Approach

Dominguez et al. [38] presented an enhancement method using wavelet decomposition. Firstly, a Gaussian smoothing filter is applied to suppress the noise; then, a top-hat operation is used to remove the background from the image. After this, the mammogram image is decomposed using wavelet transform into three scales, and the coefficients are then modified. Finally, the image is obtained using only the coefficients in the second scale, as this scale includes most of the information about the mass boundary. On the other hand, the proposed approach in [39] uses the same steps but the modification of coefficients step is conducted by employing a nonlinear function that uses the highest and lowest intensity values as information for mapping.

Figure 3.9 shows the required modification steps for the wavelet coefficients. First, it computes the mean gray value of the coefficients. Then, if the mean of a coefficient less than the specified threshold, it normalizes its value to be in range from 0 to 1. Otherwise, if the mean above the threshold, it detects the edge coefficients based on standard deviation. After that, it normalizes the detected edge coefficients, complements, and scales them by 0.5.

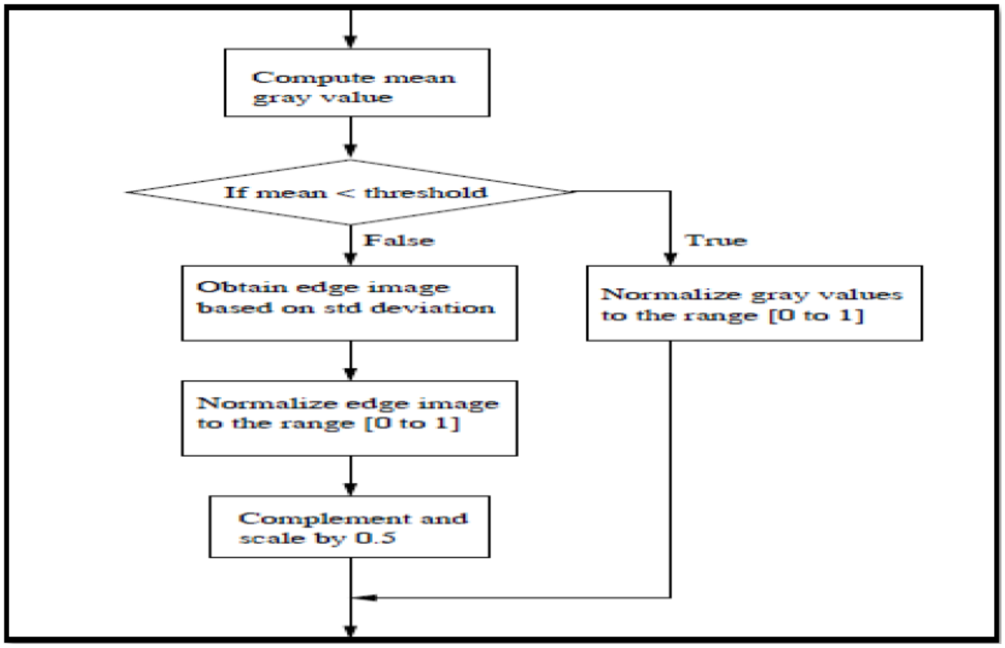


Figure 3.8: Coefficient Processing. The threshold is selected to be 0.6 for images with pixel values in the range [0, 1] [38].

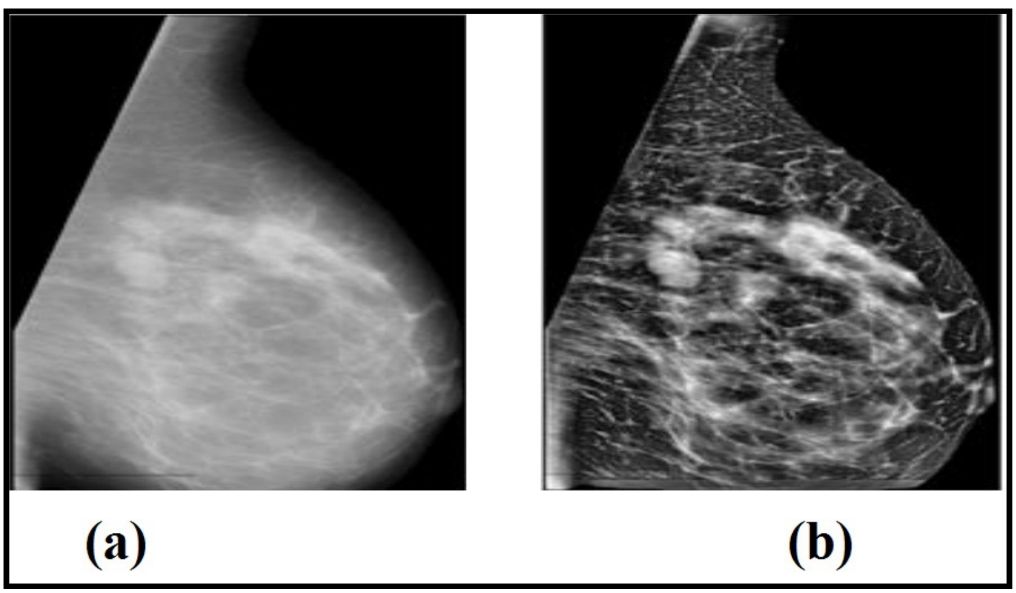


Figure 3.9: Enhancement by Dominguez method

3.3. Summary:

In this chapter, we investigated the recent proposed methods for mammogram enhancement of both microcalcifications and masses. Microcalcifications enhancement methods separated into two categories: conventional enhancement and feature-based enhancement. On the other hand, masses enhancement methods categorized as: (1) local processing approach; and (2) multi-scale processing approach. Wavelet transform have shown relatively better results. DWT DWT is not a shift invariant, which means that a shift in the original image leads to produce a different image; and this is considered the main drawback of applying DWT. DyWT overcome this issue, but it results in ringing artifacts. On the other hand, CT deals with singularities such as edges in a powerful manner and is much more robust than the DWT and DyWT. The DyWT and DWT have basis functions in only three directions, whereas CT has basis functions at various orientations but CT is not a shift invariant. NSCT is a multi-scale, multidirectional, and fully shift invariant transform.

Chapter 4

SUMMARY AND CONCLUSION

Mammography is able to reduce the mortality due to breast cancer but it is characterized by low contrast. In this report, some of the important recently proposed enhancement methods have been reviewed. Even though various enhancement methods provide almost the desired results, wavelet transform provides better enhancement results, as it has been shown in many studies.

Chapter 5

FUTURE WORKS

Enhancement of Digital Mammograms with Masses is an initiative to identify the best mammogram enhancement technique from the existing enhancement techniques.

The project aims to evaluate techniques and methods proposed in future while comparing the available methods quantitatively. Implementation of quantitative measures for better results

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