WAVELET BASED MEDICAL IMAGE ANALYSIS FOR DISEASE DIAGNOSIS

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree of

MASTER OF TECHNOLOGY

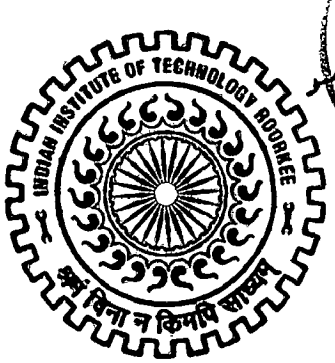
in

ELECTRICAL ENGINEERING

(With Specialization in Measurement & Instrumentation)

By

JITENDRA VIRMANI



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CANDIDATE'S DECLARATION I

I hereby declare that the work presented in this dissertation entitled **"WAVELET BASED MEDICAL IMAGE ANALYSIS FOR DISEASE DIAGNOSIS"** submitted in partial fulfillment of the requirement for the award of the Degree of **Master of Technology** in **Electrical Engineering** with specialization in **Measurement and Instrumentation,** in the Department of Electrical Engineering, **Indian Institute of Technology, Roorkee** is an authentic record of my own work carried out from July 2005 to May 2006 under the guidance and supervision of **Dr. Vinod Kumar** (Professor, Electrical Engineering Department , Indian Institute of Technology, Roorkee)

I have not submitted the matter embodied in this report for the award of any other degree or diploma.

Date: 16th June, 2006
Place: Roorkee

Jitendra Virmani 16/6/06

(Jitendra Virmani)

This is to certify that the above statement made by the candidate is true to the best of my knowledge and belief.

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Jitendra Virmani

ABSTRACT III

The area of the dissertation is medical image analysis for disease diagnosis with different algorithms which are mainly based on wavelet transformation and morphological image processing.

This dissertation report specifically gives a detailed description of the different image pre-processing and image enhancement techniques as applied to digital mammograms. The performance of different enhancement algorithms is evaluated by finding different quantitative measures such as D-Index and DV/BV ratio. Finally, the algorithms developed for detecting extremely subtle calcifications in mammograms are presented, which are very crucial to achieve the end goal i.e. classification of disease.

MIAS Mini-mammographic database is used to validate different enhancement algorithms. Because of the minute sizes of the microcalcification, the image resolution needs to be very high. The image size in mini-mammographic database has been clipped and padded to become 1,024*1,024 pixels. The dynamic range of the pixel is eight bit- that is, a gray scale of 0 to 255. Background tissues included in this database include fatty, fatty glandular, and dense glandular. The database yields abnormalities such as calcification, well defined circumscribed masses, masses with specules, ill defined masses, architectural distortion, asymmetry and normal. The ground truth of each mammogram is also included in the database, which provides the location where the abnormality is situated in terms of *(x, y, r)* within a given mammogram, where, (x, y) are the x and y axis coordinates, and r is the approximate radius of the circle enclosing the abnormality.

A cropping operation is applied to the image to prune the images with the help of crop operation in image processing. Cropping cuts of the unwanted portions of the image, thus all the unnecessary background information and most

of noise are eliminated by clipping large number of background pixels from the images, storage requirements, I/O time, and image processing time is significantly reduced.

After, the ROI has been extracted different enhancement algorithms like, histogram equalization, contrast limited adaptive histogram equalization, contrast stretching, pseudo-coloring, difference-image technique, unsharp masking, statistical based sub-band filtering and morphological enhancement are applied . The results obtained after the use of combination of techniques like unsharp masking and contrast stretch, and morphological enhancement and contrast stretch is also demonstrated.

To validate the performance of different enhancement algorithms a number of quantitative measures are proposed in the literature. The D-Index measure as proposed by Singh et. al. [29] is the only quantitative measure that uses both standard deviation and entropy in the image to evaluate the enhancement. D-Index and DV/BV ratio are used to quantitatively rank different enhancement techniques as applied to digital mammograms. It is found that morphological enhancement is the best method for enhancement of microcalcifiactions without distorting the background parencymal tissue.

For microcalcification detection, we are interested in microcalcifications of 0.05-1.0 mm in diameter, i.e. calcifications of size 1 to 5 pixels in diameter are targets to be detected. The morphologically enhanced ROI image is then presented to the algorithm that is used for detection of calcifications. Both morphological and wavelet based processing are used for detection of extremely subtle calcifications in mammograms.

Developing modules for feature extraction and classification stage are future directions in this area to develop a fully automated CAD based system for disease diagnosis. The desire to use computers in place of second radiologist, or as a pre-screener to separate out clearly normal mammograms, is the motivation for computer aided detection research.

About This Dissertation Report

Introduction- This Dissertation Report contains the entire description of the part of research done in the field of "Wavelet Based Medical Image Analysis for Disease Diagnosis".

Dissertation Report Contents- This report is divided into 8 chapters the brief introduction of each chapter is depicted here.

1. Introduction and Overview

This chapter gives a brief introduction of different concepts, the area, contribution and overview of the thesis.

2. Mammographic Image Analysis

Breast cancer is by far the most common type among women. Additionally, the etiologies of malignant breast cancer are unclear, and no single dominant cause has emerged. Although there is currently no known way of preventing breast cancer, the earlier a cancer is detected and treated, the better the prognosis. Mammography is an X-ray imaging procedure for examination of the breast. It is used primarily for the detection and diagnosis of breast cancer, but also for pre-surgical localization of suspicious areas and in the guidance of needle biopsies. The presence of microcalcification clusters (MCCs) is an important sign for the detection of early breast carcinoma.

In this chapter a block diagram of CAD system for mammographic image analysis is proposed. The need for developing such a CAD system is also highlighted.

3. Introduction to Wavelets

There are many transforms that are used quite often by engineers and mathematicians. Hilbert transform, short-time Fourier transform, Wigner distributions, the Radon Transform, and of course our featured transformation , the wavelet transform, constitute only a small portion of a huge list of transforms that are available at engineer's and mathematician's disposal.

Every transformation technique has its own area of application, with advantages and disadvantages, and the wavelet transform (WT) is no exception. In this chapter the basic concepts of wavelet theory and 2D multi-resolution analysis are discussed.

4. Wavelets Applied To Mammograms

In this chapter a wavelet based sub-band filtering method is applied to enhance the microcalcifications present in digital mammograms by inhibiting noise.

The method is based on sub-band transformation due its decomposition characteristic and includes two steps: noise inhibition and boundary enhancement. Contrast ratios are measured to evaluate the performance of enhancement algorithm.

To validate the effectiveness of the proposed technique, both conventional and proposed methods have been applied to real mammograms with microcalcifications and the enhancement performance has been compared. Results in this study demonstrate that the proposed method improves the quality of the image more than the other enhancement methods.

5. Contrast Enhancement Techniques

Contrast enhancement is one of the most important issues in image processing. We can obtain more information from the enhanced image, which will be more useful for further processing.

In mammography, early detection of breast cancer relies upon the ability to distinguish between malignant and benign mammographic features. The detection of small malignancies and subtle lesions is often difficult. In this chapter, various techniques used for mammographic image enhancement and their performance is presented. Finally, the use of combination of two enhancement techniques like, unsharp masking and contrast stretching and morphological enhancement and contrast stretching is also proposed.

6. Quantitative Measures for Contrast Enhancement

Early detection and diagnosis of breast cancer markedly increases survival rate. Accurate diagnosis also depends on the quality of the image presented to experts. This study addresses the various quantitative methods for evaluation of quality improvement of the image. CII (contrast improvement index) , (PSNR) peak signal to noise ratio, (ASNR) average signal to noise ratio, DSM (distribution separation measure) , (TBCs) Target-to-background contrast enhancement measurement based on standard deviation and (TBCe) Target–to-background contrast enhancement based on entropy have been used to evaluate the enhancement performance.

In this chapter a method to combine DSM, TBCs and TBCe into one quantitative value (D-Index) is proposed. Results in this study demonstrate that the proposed measures can be used to quantitatively rank enhancement techniques for a particular image.

7. Detection of Microcalcifications

It has been shown that early stages of breast cancer are indicated by the presence of one or more clusters of microcalcifications on the mammograms [13]. Mammogram screening increases the probability of detecting the existence of microcalcification clusters and applying the treatment appropriately. Hence, detection of microcalcification clusters with a high detection rate is crucial to the success of screening mammography. In this chapter both wavelet and morphological based techniques implemented for detecting the suspicious regions in a mammogram are explained.

8. Results and Conclusions

In this chapter, results obtained quantitatively by applying different enhancement algorithms are compared with the feedback provided by the radiologist. Nine images enhanced by seven different enhancement techniques were analyzed by a radiologist, having rich experience in reading mammograms. The feedback form presented to the radiologist, for his peer review is given in Appendix-*A*. The conclusions of the work are drawn and future directions in which the present work can be continued are discussed.

Image Data Sources

Resource	URL/Description
MIAS database	Mammographic Image Analysis Society Mini-mammographic database. Organizer: J Suckling, Truth-Data: C R M Boggis http://skye.icr.ac.uk/miasdb/miasdb.html
Mc-Gill database	http://sprojects.mmi.mcgill.ca/mammography/

Conventions

This dissertation report uses the following conventions.

Typographical

The following typographical conventions are used in this report.

Conventions	Meaning or Usage
Century	Chapter main heading
Franklin Gothic Medium	Introduction to chapter
Georgia	Title / sub-title
Times New Roman	Title/ sub-title Body
Times New Roman	Description of figures and tables
Franklin Gothic Medium	Results/Conclusions
Square Brackets [ ]	References

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ABBREVIATIONS AND ACRONYMS VII

A

ACR	American College of Radiology
ASNR	Average Signal to Noise Ratio

B

BIRADS	Breast Imaging Reporting and Data System
BSE	Breast Self Examination
BV	Background Variance
BV/DV	Background Variance/Detail Variance

C

CAD	Computer Aided Diagnosis
CAT	Computer Axial Tomography
CII	Contrast Improvement Index
CIR	Contrast Improvement Ratio
CLAHE	Contrast Limited Adaptive Histogram Equalization
CME	Convolution Mask Enhancement
CS	Contrast Stretching

D

DCIS	Ductal Carcinoma in Situ
DSM	Distribution Separation Measure
DV	Detail Variance

	DWT	Discrete Wavelet Transform
F		
	FN	False Negative
	FP	False Positive
	FT	Fourier Transform
	FP	
G		
	GUI	Graphic User Interface
H		
	HISTEQ	Histogram Equalization
I		
	I/O	Input/Output
M		
	MCC's	Microcalcifications
	ME	Morphological Enhancement
	MIAS	Mammographic Image Analysis Society
	MRA	Multi Resolution Analysis
	MRI	Magnetic Resonance Imaging
P		
	PC	Pseudo-Coloring
	PGIMER	Post Graduate Institute of Medical Education and Research.
	PR-QMF	Perfect Reconstruction Quadrature Mirror Filters
	PSNR	Peak Signal to Noise Ratio

Q

QMF	Quadrature Mirror Filters

R

ROI	Region of Interest

S

STFT	Short Time Fourier Transform

T

TBCe	Target to Background Contrast Enhancement Index based on Entropy
TBCs	Target to Background Contrast Enhancement Index based on Standard deviation

U

UM	Unsharp Masking

W

WL	Wavelet Based Sub-Band Filtering
WT	Wavelet Transform

TABLE OF CONTENTS

Chapter 1

INTRODUCTION AND OVERVIEW

Introduction- This chapter gives a brief introduction of different concepts, the area, contribution and overview of the thesis.

The brief overview of different applications of digital image processing in general and medical image processing in particular are cited. The basic principle of different imaging modalities used are discussed. Definitions and terminology used in mammography is described. Attempt has been made to present before the reader, the characteristics of different benign and malignant calcifications, the difficulties encountered in detecting extremely subtle micro calcifications. Finally, the area and the contribution of the thesis are highlighted.

Literature Survey-

Diagnostic features in mammograms vary widely in size and shape. Classical image enhancement techniques cannot adapt to the varying characteristics of such features. The fundamental enhancement needed in mammography is an increase in contrast, especially for the dense breasts. Contrast between malignant tissue and normal dense tissue may be present on a mammogram, but below, the threshold of human perception. As well, calcifications in a sufficiently dense mass may not be readily visible because of low contrast, so that defining the characteristics of calcifications is difficult. Consequently, computer- assisted enhancement of mammograms for detection of microcalcifiactions arouse a great deal of interest.

Adaptive histogram equalization has been shown to enhance contrast in radiological images, which in general have a large global dynamic range, but small local feature gray level variations [34]. Locally adaptive histogram equalization performs histogram equalization independently over different segments of the image.

Ideally, the area of the image immediately surrounding a given pixel is used to calculate a histogram, which is then equalized to give the new pixel value. This procedure is computationally very intensive. The often radically different appearance of the image after the equalization may be undesirable in some classes of images, including mammograms.

Local enhancement techniques use statistical properties in the neighborhood of the pixel to estimate the background, suppress it and increase local contrast. Lee [34] calculates the local mean and variance, and performs a transformation to a desired local mean and variance. In these methods, determination of local neighborhood dimensions is a critical step. A given neighborhood size and shape may not be equally effective in enhancing all areas of an image.

Convolution masking is one of the most commonly used methods of digital image enhancement. The unsharp mask operation actually consists of performing several operations in series on the original image. First we blur the original image and then subtract the blurred image from the original (the resulting difference image is called the *'mask'*. Finally, we add the mask to the original. The processed image is sharper because low frequency information in the image is reduced in intensity while high frequency details are amplified. This makes microcalcifications more visible in mammograms.

Enhancement by background removal is a direct method of reducing the slowly varying portions of an image, to allow increased gray level variations in the image details. It is usually performed by subtracting the low pass filtered version of the image from itself.

Unsharp masking is a simple version of this procedure. Spline filtering and gray scale morphological processing are two methods of estimating the image background. The background extraction technique should be adaptive to the local image characteristics to truly identify the image background.

Digital unsharp masking [3], and statistical band pass filtering [45] have been used to enhance mammograms. The approach taken by these methods is to enhance difficult mammograms to sufficient quality to allow the radiologist to make his diagnosis with more confidence. More work has been done on analysis of mammograms, for identification of image features associated with cancer. Automated detection of tumors have been investigated [16-20], although few studies [17] have tested their methods on large number of cases.

Mathematical morphology methods- Morphological operations can be employed for many image processing purposes, including edge detection, segmentation, and enhancement of images [45]. The simplicity of the mathematical morphology comes from the fact that a large class of filters can be represented as the combination of two simple operations on the image; the erosion and dilation [45]. The opening is erosion followed by dilation and closing is a dilation followed by erosion. These two operations are considered as filters. To enhance mammograms two operations have been used; the top-hat transform defined as the difference between the original image and its opening, and the bottom-hat transform defined as the difference between the closing of the original image and the original image. Operations of addition and subtraction of images are then carried out using the top-hat and bottom-hat transforms to obtain a mammographic image containing much more visible microcalcifications.

Many digital image enhancement algorithms have been developed and were reviewed in [3]. These techniques generally enhance image contrast, but they simultaneously amplify noise and artifacts. In interpreting mammograms, noise and artifacts are undesirable and can potentially lead to false diagnoses.

The superiority of the wavelet transform for enhancing the contrast in digital medical images is well established [18-24].It is an extremely powerful data representation method that allows for the separation of images into frequency bands without effecting the spatial locality, Thus, information concerning localized high-frequency signals can be extracted effectively.

This multi-scale representation provides the flexibility to enhance image objects of various sizes and enables noise magnification to be controlled. Several methods, based on wavelet transformation, have also been presented for noise reduction and enhancement by thresholding the wavelet coefficients [21-24]. The fundamental characteristics of these methods are that no spurious oscillations are introduced and the boundary information in the image is preserved.

Evaluation of Enhancement- The improvement in the images after enhancement is often very difficult to measure. A processed image can be said to be an enhancement over the original image if it allows the observer to better perceive the desired information in the image. In mammograms, the improved perception is difficult to quantify.CII (contrast improvement index) , CIR (contrast improvement ratio) , (PSNR) peak signal to noise ratio, (ASNR) average signal to noise ratio, DSM (distribution separation measure) , (TBCs) Target-to-background contrast enhancement measurement based on standard deviation and (TBCe) Target -to-background contrast enhancement based on entropy have been used to evaluate the enhancement performance. A method to combine DSM, TBCs and TBCe into one quantitative value called D-Index is also proposed by Singh et. al. [29]

Both morphological based processing and Wavelet based processing have been applied for detection of calcifications sin mammograms. Morphological based processing uses opening and closing filters, sobel and canny edge detectors and flood filling to enhance calcifications. Wavelet based processing, utilizes the fact that microcalcifiactions are small, bright features, and they, therefore appear in certain levels of wavelet decompositions of the image.

In the work that is presented in this report, the performance of different enhancement algorithms for enhancing microcalcifications have been tested by finding out different quantitative measures like D-index and DV/BV ratio.

The performance of both morphological based and wavelet based methods for MCC detection is also reported.

1.1 Definitions and Terminology

1.1.1 Image Processing

Image processing is a form of information processing for which both the input and output are images, such as photographs or frames of video. Most of the image processing techniques involve treating the image as a two-dimensional signal and applying standard signal processing techniques to it.

1.1.2 Digital Image Processing

Digital image processing is the use of computer algorithms, to perform image processing on digital images.

In particular, digital image processing is the only practical technology for-

- Classification
- Feature extraction
- Pattern recognition
- Projection
- Multi-scale signal analysis

1.1.3 Medical Imaging

Medical imaging is the process by which physicians evaluate an area of the subject's body that is not externally visible.

Medical imaging may be clinically motivated, seeking to diagnose and examine disease in specific human patients. Alternatively, it may be used by researchers in order to understand processes in living organisms. Many of the techniques developed for medical imaging also have scientific and industrial applications.

Medical imaging often involves the solution of mathematical inverse problems. This means that cause (the properties of living tissue) is inferred from effect (the observed signal).

In the case of ultrasonography the probe consists of ultrasonic pressure waves and echoes inside the tissue, show the internal structure. In the case of

radiography, the probe is x-ray radiation which is absorbed at different rates by different types of tissue such as bone, muscle and fat.

1.1.4 Imaging Modalities

Radiography-

Radiographs, more commonly known as x-rays, are often used to determine the type and extent of a fracture as well as for detecting pathological changes in the lungs. With the use of radio-opaque contrast media, such as barium, they can also be used to visualize the structure of the stomach and intestines - this can help diagnose ulcers or certain types of colon cancer.

Fluoroscopy-

Fluoroscopy produces real-time images of internal structures of the body in a similar fashion to radiography, but employs a constant input of x rays. Contrast media, such as barium, iodine, and air are used to visualize internal organs as they work. Fluoroscopy is also used in image-guided procedures, where constant feedback during a procedure is required.

Tomography-

Tomography is the method of showing a single plane, or slice, of an object. There are several forms of tomography-

- Linear Tomography
- Poly Tomography
- Computed Tomography (CAT or CT)

A CT scan, also known as a CAT scan (computed axial tomography scan), is a helical tomography, which traditionally produces a 2D image of the structures in a thin section of the body. It uses x-ray, which is ionizing radiation.

Magnetic Resonance Imaging-

An MRI uses powerful magnets to excite hydrogen nuclei in water molecules in human tissue, producing a detectable signal. Like a CT scan, an MRI traditionally creates a 2D image of a thin slice of the body. The difference between a CT image and an MRI image is in the details. In CT scan, X-rays must be blocked by some form of dense tissue to create an image, therefore the image quality when looking at soft tissues will be poor.

An MRI can only see hydrogen based objects, so bone, which is calcium based, will be a void in the image, and will not affect soft tissue views. This makes it excellent for peering into joints. As an MRI does not use ionizing radiation, it is the preferred imaging method for children and pregnant women.

Ultrasound-

Medical ultrasonography uses high frequency sound waves of between *2.0 to 10.0 megahertz* that are reflected by tissue to varying degrees to produce a 2D image, traditionally on a TV monitor. This is often used to visualize the fetus in pregnant women. Other important uses include, imaging the abdominal organs, heart, and the veins of the leg.

While US may provide less anatomical information than other techniques such as CT or MRI, it has several advantages which make it ideal as a first line test in numerous situations, in particular that it studies the function of moving structures in real-time. It is also very safe to use, as the patient is not exposed to radiation and the ultrasound does not appear to cause any adverse effects. It is also relatively cheap and quick to perform. The real time moving image obtained can be used to guide drainage and biopsy procedures.

Xeroradiography-

The prefix xero- comes from the Greek word *xeros* meaning *dry*. Xeroradiography is a photoelectric method of recording an x-ray image on a coated metal plate. It using low-energy photon beams, long exposure time and dry chemical developers.

Creation of three-dimensional images

Recently, techniques have been developed to enable CT, MRI and Ultrasound scanning software to produce 3D images for the physician. Traditionally CT and MRI scans produce 2D static output on film. To produce 3D images, many scans are made, which are then combined by computers to produce a 3D model, which can then be manipulated by the physician. 3D ultrasounds are produced using a some what similar technique.

With the ability to visualize important structures in great detail, 3D visualization methods are a valuable resource for the diagnosis and surgical treatment of many pathologies.

1.2 Mammogram

A mammogram is an x-ray test that produces an image of the inner breast tissue on film. *Fig-1.1* below shows a digital mammogram image.

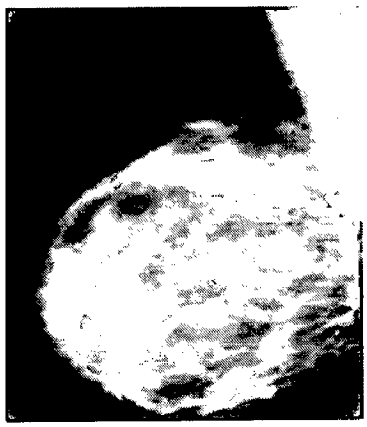
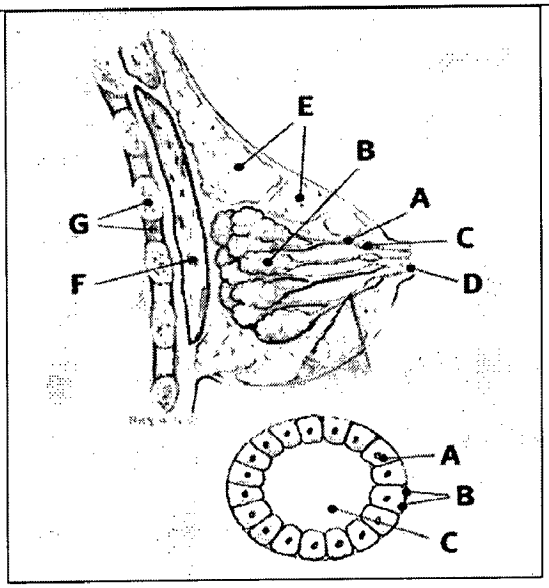


Fig-1.1- Digital mammogram

1.2.1 Anatomy of Breast Tissue

Fig-1.2 shows below the anatomical features of the breast tissue



- **A** ducts
- **B** lobules
- **C** dilated section of duct to hold milk
- **D** nipple
- **E** fat
- **F** pectorals major muscle
- **G** chest wall/rib cage
- **Enlargement:**
- **A** normal duct cells
- **B** basement membrane
- **C** lumen (center of duct)

Fig-1.2- Anatomy of breast tissue[37]

1.2.2 Internal features of the breast

The lobules and ducts in the breast are supported by surrounding fatty tissue and the suspensory ligaments of the breast. There are no muscles in the breast. The characteristic bounce of the breast comes from the elasticity of the matrix of connective tissue fibers in the breast.

There are blood vessels and lymphatics in the breast. The lymphatics are thin channels similar to blood vessels; they do not carry blood but collect and carry tissue fluid which ultimately reenters the blood stream. Breast tissue fluid drains through the lymphatics into the lymph nodes located in the underarm (axilla) and behind the breast bone (sternum).

1.2.3 Symptoms of breast cancer

Breast cancer in early stages usually, does not cause pain. In fact, when breast cancer first develops, there may be no symptoms at all.

But as the cancer grows, the following symptoms generally occur-

- A lump or thickening in or near the breast or in the underarm area.
- A change in the size or shape of the breast.
- Nipple discharge or tenderness, or the nipple pulled back (inverted) into the breast.
- Ridges or pitting of the breast (the skin looks like the skin of an orange).
- A change in the way the skin of the breast, areola, or nipple looks or feels (for example, warm, swollen, red, or scaly).

1.2.4 Mammography

It is a technique, used to visualize normal and abnormal structures within the breasts. Mammography, therefore, can help in identifying cysts, calcifications, and tumors within the breast.

Mammography is currently the most effective way to detect early breast cancer. Breast self- examination (BSE) on a monthly basis and examination by a doctor are still important, but physical examinations typically find breast cancers when they are much larger than those detected by mammography [40]. While mammography can discover a small cancer in a curable stage.

Ten to fifteen percent of breast cancers are not identified by mammography and these cancers are found by physical examination. It is essential for a woman to perform monthly BSE and have a breast examination

by her doctor in addition to the mammogram in order to most effectively screen for breast cancer.

1.2.5 Definitions of terms associated with mammography

Microcalcifications

Tiny calcium deposits less than 1/50 of an inch in size. When many microcalcifications are seen in one area, they are referred to as a cluster and may indicate a small cancer. About half of the cancers detected by mammography appear as a cluster of microcalcifications. Microcalcifications are the most common mammographic sign of ductal carcinoma in situ (DCIS), (cancer that has not spread into neighboring breast tissue). Almost 90% of cases of DCIS are associated with microcalcifications.

Macrocalcifications

Larger, coarse calcium deposits that are often related to benign (non-cancerous) growths such as fibroadenomas or with degenerative changes in the breasts, such as aging of the breast arteries, old injuries, or inflammation. Macrocalcifications are usually associated with benign (non-cancerous) conditions and may not require a biopsy [40]. They are found in one out of two women over the age of 50.

Dense, Density

Dense breast tissue has many glands close together. Density shows up as a white area on a mammogram film. Though fairly common (especially in younger women), dense breasts may make microcalcifications and many other masses difficult to detect.

Asymmetry

An area that is not found to be identical in both breasts (such as density). It is often a normal variant but can also be a sign of an abnormal growth.

Cyst

Cyst is a fluid-filled mass. Simple cysts are benign (non-cancerous). Ultrasound is often used to confirm the presence of a cyst. Sometimes, cysts are drained with a fine needle aspiration biopsy.

Monomorphic

Monomorphic often describes microcalcifications that are uniform in shape and density (and usually non-cancerous).

Pleomorphic, Polymorphic or Multiform

Having an irregular shape or various shapes.

Lesion

A wound, injury, or other damage to a body part. Breast tumors are often referred to as lesions.

Spiculated

On a mammogram, dense regions with radiating lines suggest the presence of breast masses or distortions. The term is used to describe highly suspicious masses that may indicate cancer.

Mass, Lump or Nodule

A structure that can be felt when the breast is examined. Usually further evaluated with mammography and/or other breast imaging tests.

Radiodense, Radiopaque

Effective in blocking x-rays. Breast tissue in younger women is usually more *radiodense* than the fattier tissue in older women.

Palpable

A breast lump that can be felt by hand.

Suspicious

A breast abnormality that may indicate breast cancer. On a mammogram, these abnormalities may be lesions such as spiculated masses or pleomorphic microcalcifications.

Parenchyma, Parenchymal

The functional tissue of an organ. In the breast, it is the glandular tissue (as opposed to fatty or stromal (connective) tissues).

Unilateral

Occurring on or in only one breast.

Bilateral

Occurring on or in both breasts.

1.2.6 Difficulties encountered in microcalcification detection

Problems encountered in detecting the microcalcifications on the mammographic images are given below :-

- High variety of microcalcifications
- High variability of background
- Gradual variations in mammographic signs

Fig-1.3 below shows high variability of background in mammographic images

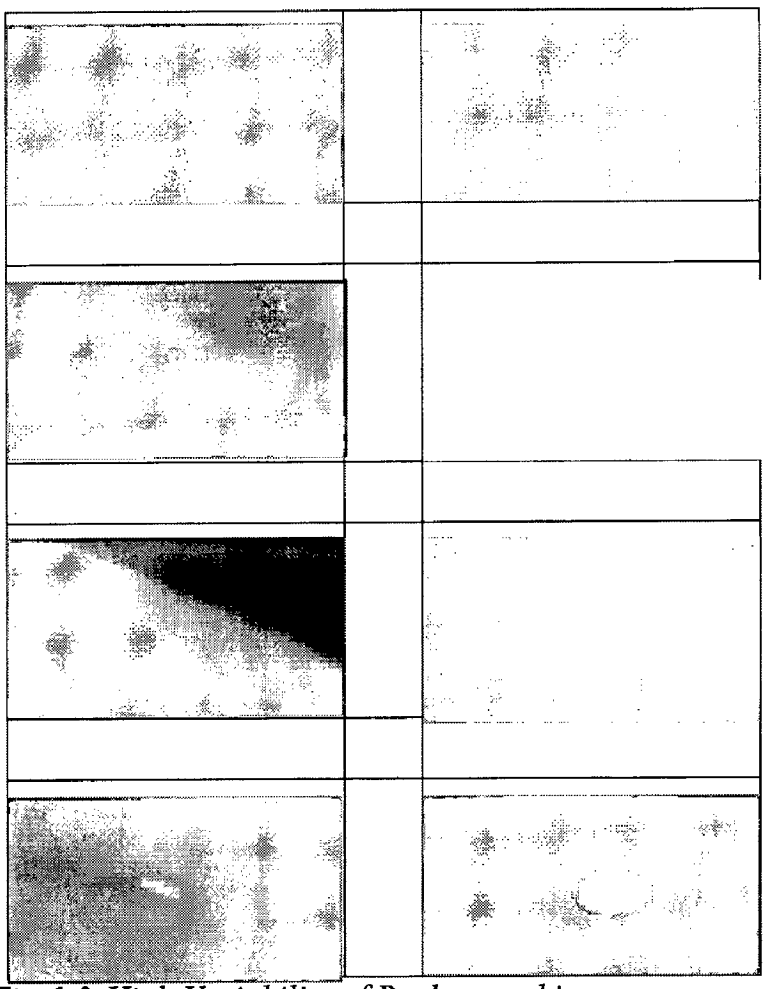
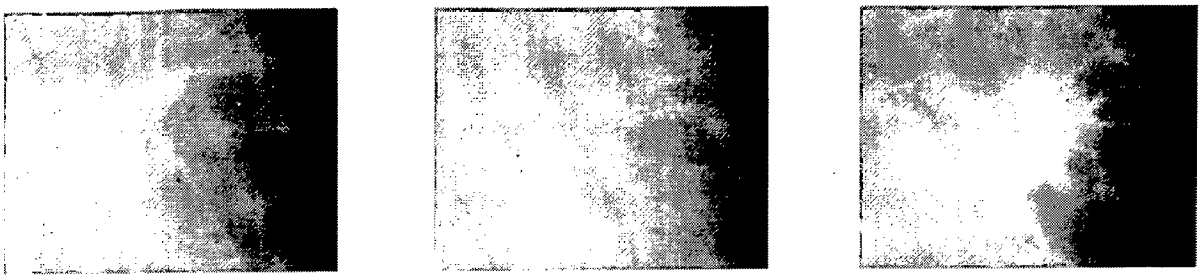


Fig-1.3-High Variability of Background in mamograms

Fig-1.4 below shows the changes in mammographic signs over a period of time-



1992 1995 1999

Fig-1.4- Variations in Mammographic Signs

1.2.7 Characteristics of benign and malignant calcifications

Fig-1.5 below shows the characteristics of benign and malignant calcifications in terms of their margin, shape and density.

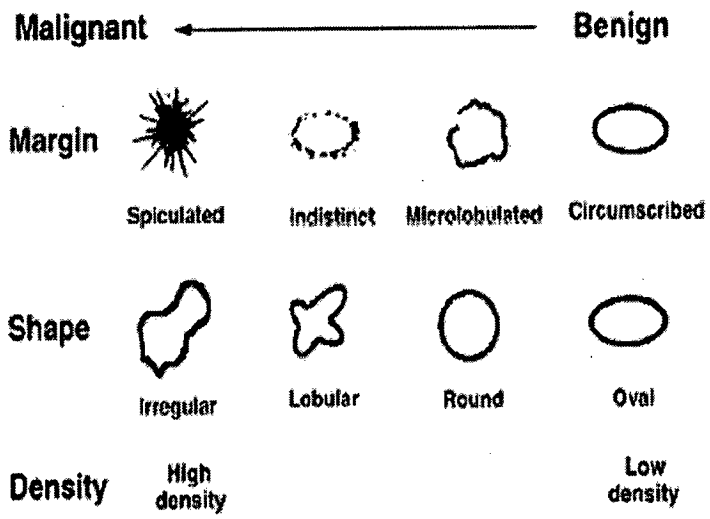


Fig-1.5- Characteristics of benign and malignant calcifications [39]

1.3 Area of the Thesis

The ultimate goal of the thesis is to find out the most suitable method for enhancing the region of interest in digital mammograms and to effectively detect the extremely subtle calcifications hidden in heterogeneous parenchymal tissue.

1.4 Contribution of the Thesis

The algorithms developed for enhancing and detecting subtle calcifications in digital mammograms serve as significant modules for developing a fully automated CAD based mammographic image analysis system.

Chapter 2

MAMMOGRAPHIC IMAGE ANALYSIS

Introduction- Breast cancer is by far the most common type among women. Additionally, the etiologies of malignant breast cancer are unclear, and no single dominant cause has emerged. Although there is currently no known way of preventing breast cancer, the earlier a cancer is detected and treated, the better the prognosis [37]. Mammography is an X-ray imaging procedure for examination of the breast. It is used primarily for the detection and diagnosis of breast cancer, but also for pre-surgical localization of suspicious areas and in the guidance of needle biopsies. Breast cancer is detected on the basis of four types of signs observed on the mammograms:

1. The characteristic morphology of a tumor mass.
2. Certain presentations of mineral deposits as specks called microcalcifications
3. Architectural distortion of normal tissue patterns caused by disease.
4. Asymmetry between corresponding regions of images of the left and the right breast.

The presence of microcalcification clusters (MCCs) is an important sign for the detection of early breast carcinoma.

In this chapter a block diagram of CAD system for mammographic image analysis is proposed. The need for developing such a CAD system is also highlighted.

2.1 Mammographic Abnormalities

A radiologist looks for certain signs and characteristics indicative of cancer when evaluating a mammogram. Masses and calcifications are most common abnormalities on mammograms. A mass is a space-occupying lesion seen in at least two mammographic

projections. A calcification is deposit of calcium salt on tissue. Both can be associated with either benign or malignant abnormalities, and can have a variety of appearances. The American College of Radiology (ACR) formulated Breast Imaging Reporting and Data System (BI-RADS), which contains a guide to standardized mammographic reporting, including a breast-imaging lexicon of terminology, a report organization and assessment structure and coding system, to help in standardized reporting [37]. The lexicon used for describing mammographic abnormalities is organized by mass and calcifications.

Masses are described by their geometry, border characteristics, and density. Calcifications are described by their size morphology and distribution. The ACR-BIRADS has classified findings of calcifications into three categories: (1) Typically benign; (2) Intermediate concern; and (3) Higher probability of malignancy.

2.1.1 Masses

The shape of the mass can be round, oval, lobular, or irregular, and its margins can be circumscribed, microlobulated, obscured, indistinct, or spiculated. Both shape and margins are indicators of the likelihood of malignancy with round and oval shapes and circumscribed margins having a lower likelihood of malignancy. Architectural distortions are another secondary sign of cancer. *Fig-2.1* shows two examples oval mass and a round mass with circumscribed margins.

2.1.2 Calcifications

Calcifications are often important and common findings on a mammogram. They can be produced from cell secretion or from necrotic cellular debris.

They may be intra-mammary, within and around the ducts, within the lobules, in vascular structures, in interlobular connective tissue or fat. Alternatively, they may be found in the skin. They can appear with or without an associated lesion, and their morphologies and distribution provide clues as to their etiology as well as whether they can be associated with a benign or malignant process.

Typical benign types include, skin, vascular, coarse, large rod like, round, spherical, or lucent centered, eggshell, milk of calcium, suture, dystrophic, or punctate.

amorphous or indistinct types are of more intermediate concern. Pleomorphic or heterogeneous and fine branching calcification types indicate a high probability of malignancy. The type is modified by the keywords that indicate the distribution of the calcifications.

The distribution can be clustered, linear, segmental regional, or diffuse (scattered). Regional or diffuse distributions are more likely to be benign.

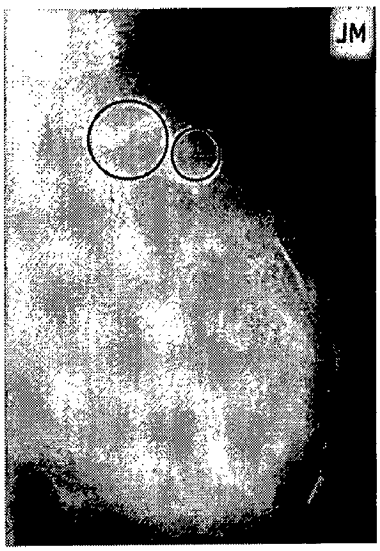


Fig-2.1- A mammogram with an oval mass and a round mass with circumscribed margins evident in the upper quadrant (shown in circles) of the ML view of the breast.

Calcifications found with a mass provide further information about that particular mass. For example, an involuting fibroadenoma will often contain popcorn-like macrocalcifications. Similarly, fine curvilinear calcifications at the margin (i.e. rim calcifications) of a round or oval mass indicate a benign process. On the other hand, a mass with pleomorphic, irregularly shaped calcifications heterogeneous in size and morphology raises much greater concern about malignancy.

Calcifications are analyzed according to their size, shape, number, and distribution. The general rule is that larger, round or oval shaped calcifications uniform in size has a higher probability of being associated with a benign process and smaller, irregular, polymorphic, branching calcifications heterogeneous in size and morphology are more often associated with a malignant process.

Certain calcification patterns are almost always pathognomic of a benign process, and in such cases no further analysis is needed. In the majority of cases, however, a pattern of calcification deposition is inconclusive and may be attributable to either a benign or malignant process. Needless to say, these cases require additional evaluation such as using magnification mammography to further elucidate the calcifications' morphology and distribution.

2.1.3 Characteristics of Benign Calcifications

Benign calcifications are more likely to be round, similar in size and shape, and to be regional or diffuse/scattered.

They often are bilateral if asymmetric. Benign calcifications are frequently seen in a lobular or ductal distribution.

Fig-2.2 shows a mammogram with cluster of microcalcifications in two different views.

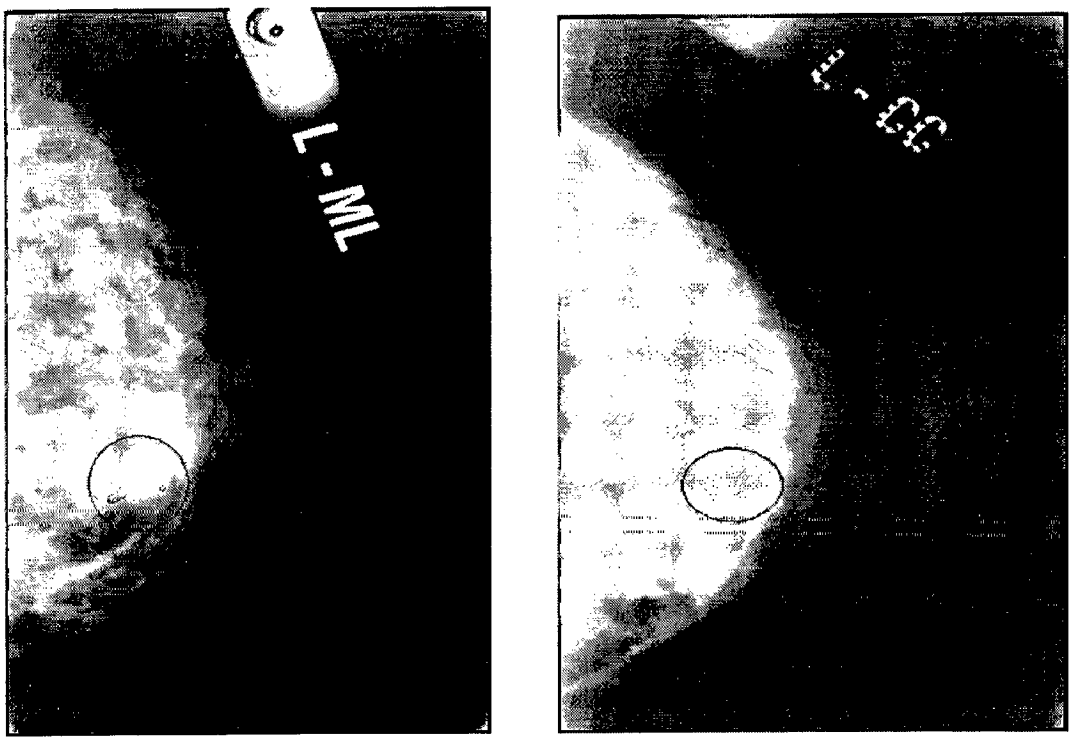


Fig-2.2- A Mammogram with cluster of microcalcifications in two different views (Circular areas contain microcalcifications).

2.1.4 Characteristics of Tumor Calcifications

(a) Size

Generally speaking, *microcalcifications* are associated with a malignant process and *macrocalcifications* are associated with a benign process. The problem with this general rule is that there is no fine line of measurement that could enable one to distinguish between micro and macro. All calcifications start out imperceptibly small and radiographically invisible. Most radiologists place calcifications 0.5 mm or less to have a high probability of association with cancer; and calcifications of 2.0 mm or larger are typical of a benign process. The smallest visible calcifications on a mammogram are approximately 0.2-0.3 mm.

(b) Number

The number of calcifications that make up a cluster has been used as an indicator of benign and malignancy. While the actual number itself is arbitrary, radiologists tend to agree that the minimum number of calcifications be four, five, or six to be of significance. Any number of calcifications less than four will rarely lead to the detection of breast cancer in and of itself. Again, as with all criteria in mammographic analysis, no number is absolute and two or three calcifications may merit greater suspicion if they exhibit worrisome morphologies. Most characteristic of carcinoma is countless category. Numerically more then 10 calcifications are clustered it is taken to be malignant.

(c) Morphology

The morphology of calcifications is considered to be the most important indicator in differentiating benign from malignant. As noted earlier, round and oval shaped calcifications that are also uniform in shape and size are more likely to be on the benign end of the spectrum. Calcifications that are irregular in shape and size fall closer to the malignant end of the spectrum. It has been described that calcifications associated with a malignant process resemble small fragments of broken glass and are rarely round or smooth.

2.2 Proposed Cad System

Several methodologies have been developed in order to improve radiologists' efficiency in the diagnostic interpretation of mammograms. The successful development

of computer aided diagnosis (CAD) systems would be of great value, if these systems can provide a reliable second opinion to the radiologist.

The main goal of this work is to make contributions to a computer aided diagnosis system, which can provide a "second opinion" to radiologists on a routine clinical basis.

The problem of mammogram interpretation can be decomposed into two sub-problems. The first deals with the detection and localization of suspicious regions of interest (ROI's) containing microcalcifications.

The second, and more difficult sub-problem, is the characterization of the suspected microcalcifications as malignant or benign. A successful characterization could contribute to the reduction of unnecessary biopsies. The abstract view of the work done for the proposed computer aided diagnosis (CAD) based system is highlighted in the block diagram shown in *Fig-2.3* below.

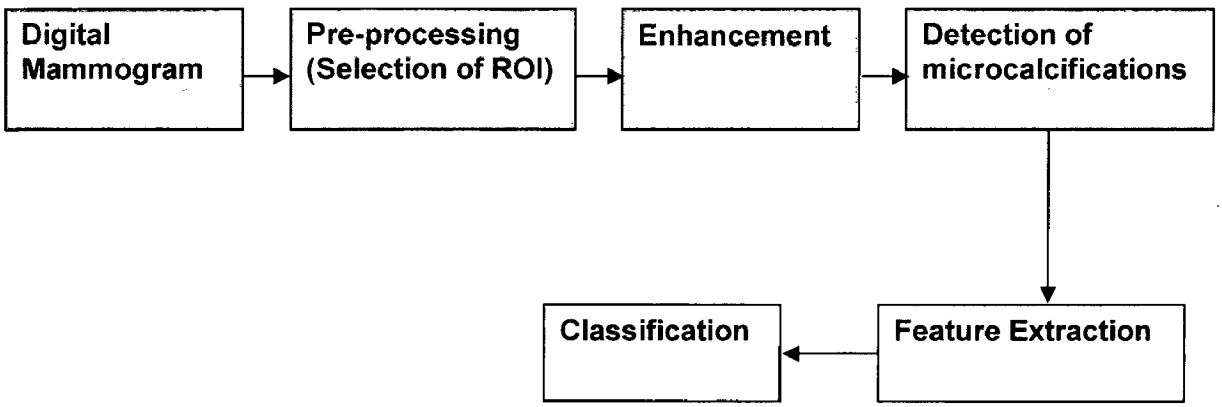


Fig-2.3- Block diagram showing the work done for proposed computer-aided diagnosis (CAD) system [16].

The very first step in the system is selection or marking of ROI on mammogram by the expert radiologist. Then, the ROI selected from the digitized mammogram are de-noised and enhanced. The detection of microcalcifications block is designed to find suspicious areas containing MCCs, and to separate the MCCs from the background that will be used for extracting features of MCCs. In the feature extraction and selection block, the features of MCCs will be extracted, and finally MCCs will be classified into benign, malignant using any classifier.

Different techniques of image pre-processing, mammogram image enhancement are described in chapter 5, quantitative measures to evaluate the performance of different enhancement techniques are described in chapter 6. The algorithms used for detecting microcacifications are discussed in chapter 7.

The desire to use computers in place of second radiologist, or as a pre-screener to separate out clearly normal mammograms, is the motivations for computer aided detection research [16].

Chapter 3

AN OVERVIEW OF THE WAVELET THEORY

Introduction- **There are many other transforms that are used quite often by engineers and mathematicians. Hilbert transform, short-time Fourier transform (more about this later), Wigner distributions, the Radon Transform, and of course our featured transformation , the wavelet transform, constitute only a small portion of a huge list of transforms that are available at engineer's and mathematician's disposal. Every transformation technique has its own area of application, with advantages and disadvantages, and the wavelet transform (WT) is no exception. This chapter presents before the reader the basic concepts of wavelet theory and 2D multi-resolution analysis.**

3.1 Transformation

Mathematical transformations are applied to signals to obtain further information from that signal that is not readily available in the raw signal. In this chapter a time-domain signal is assumed as a *raw* signal, and a signal that has been "transformed" by any of the available mathematical transformations is assumed as a *processed* signal.

Most of the signals in practice are time-domain signals in their raw format. That is, whatever that signal is measuring, is a function of time. In other words, when we plot the signal one of the axes is time (independent variable), and the other (dependent variable) is usually the amplitude. When we plot time-domain signals, we obtain a time-amplitude representation of the signal. This representation is not always the best representation of the signal for most signal processing related applications. In many cases, the most distinguished information is hidden in the frequency content of the signal.

The *frequency spectrum* of a signal is basically the frequency components of a signal. The frequency spectrum of a signal shows what frequencies exist in the signal.

3.2 Fourier Transform (FT)

To find the frequency content of a signal, Fourier transforms are probably by far the most popular. If the FT of a signal in time domain is taken, the frequency-amplitude representation of that signal is obtained. In other words, we now have a plot with one axis being the frequency and the other being the amplitude. This plot tells us how much of each frequency exists in our signal.

For example, if we take the FT of the electric current that we use in our houses, we will have one spike at 50 Hz, and nothing elsewhere, since that signal has only 50 Hz frequency component. No other signal, however, has a FT which is this simple. For most practical purposes, signals contain more than one frequency component.

The following equations can be used to calculate the Fourier transform of a time-domain signal and the inverse Fourier Transform [8]:

$$X(f) = \int_{-\infty}^{+\infty} x(t) e^{-2j\pi ft} \partial t \qquad (3.1)$$

$$X(t) = \int_{-\infty}^{+\infty} x(f) e^{2j\pi ft} \partial f \qquad (3.2)$$

Fourier transforms are very useful at providing frequency information that cannot be seen easily in the time domain. However they do not suit brief signals, signals that change suddenly, or in fact any nonstationary signals.

The reason is that they show only what frequencies occur, not when these frequencies occur, so they are not much help when both time and frequency information is required simultaneously. In stationary signals, all frequency components occur at all times, so Fourier Transforms are very useful.

3.3 Why do we need frequency information?

While analyzing biological signal, pathological condition may not always be quite obvious in the original time-domain signal. A pathological condition can sometimes be diagnosed more easily when the frequency content of the signal is analyzed.

Today Fourier transforms are used in many different areas including all branches of engineering. Although FT is probably the most popular transform being used (especially in electrical engineering), it is not the only one. There are many other transforms that are used quite often by engineers and mathematicians. Hilbert transform, short-time Fourier transform (more about this later), Wigner distributions, the Radon Transform, and of course our featured transformation , the wavelet transform, constitute only a small portion of a huge list of transforms that are available at engineer's and mathematician's disposal. Every transformation technique has its own area of application, with advantages and disadvantages, and the wavelet transform (WT) is no exception.

3.4 Reversible Transformation

FT (as well as WT) is a reversible transform, that is, it allows to go back and forward between the raw and processed (transformed) signals. However, only either of them is available at any given time. That is, no frequency information is available in the time-domain signal, and no time information is available in the Fourier transformed signal.

In other words, the frequency content of stationary signals do not change in time. In this case, one does not need to know at what times frequency components exist, since all frequency components exist at all times.

3.5 Short Time Fourier Transform (STFT)

The main drawback of FT is that it did not work for non-stationary signals. To overcome this problem we assume that, some portion of a non-stationary signal is stationary. If this region where the signal can be assumed to be stationary is too small, then we look at that signal from narrow windows, narrow enough that the portion of the signal seen from these windows are indeed stationary.

The STFT looks at a signal through a small window, using the idea that a sufficiently small section of the wave will be approximately a stationary wave and so Fourier analysis can be used.

The window is moved over the entire wave, providing some information about what frequencies appear at what time. *Fig-3.1* below shows a window used for STFT.

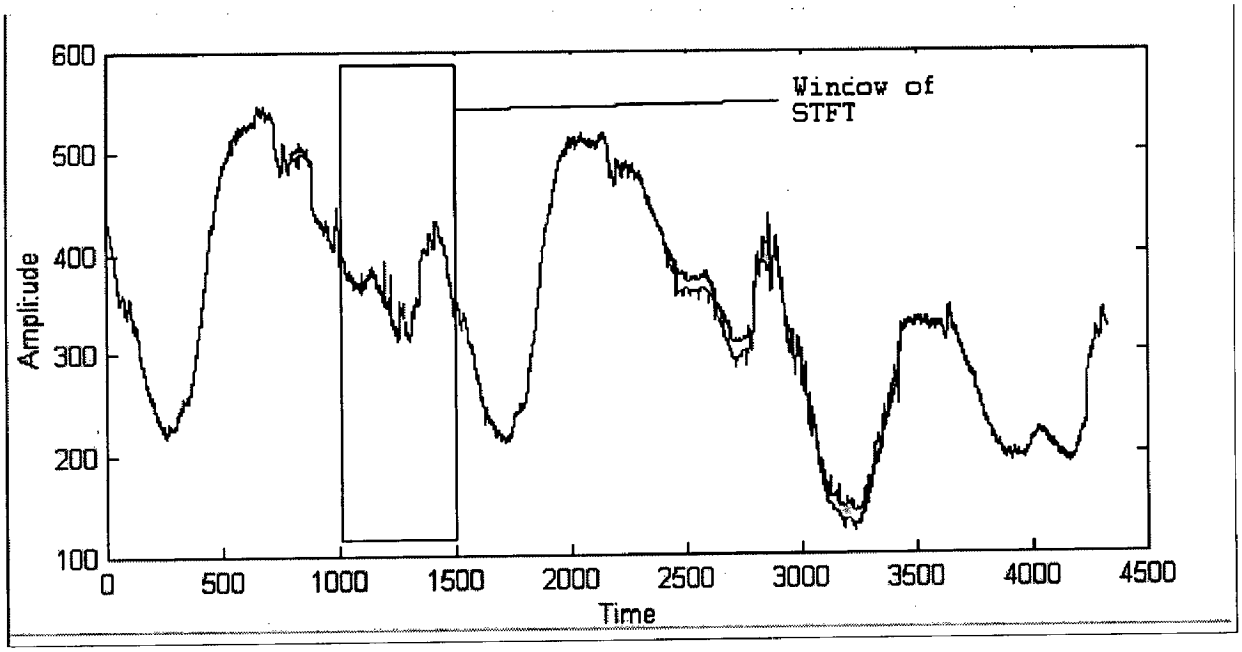


Fig-3.1- Example of window used for STFT

The equation 3.3 below can be used to compute a STFT. It is different to the FT as it is computed for particular windows in time individually, rather than computing overall time (which can be alternatively thought of as an infinitely large window). x is the signal, and w is the window.

$$STFT_x^w(t,f) = \int [x(t) * w^*(t-t')] e^{-j2\pi ft} \partial t \quad (3.3)$$

The problem with the STFT has something to do with the width of the window function that is used. The width of the window function is known as the support of the window. If the window function is narrow, than it is known as compactly supported.

STFT gives the TFR of the signal. The problem with STFT is the fact whose roots go back to what is known as the Heisenberg Uncertainty Principle. This principle originally applied to the momentum and location of moving particles, can be applied to time-frequency information of a signal. Simply, this principle states that one cannot know the exact time-frequency representation of a signal, i.e., one cannot know what spectral components exist at what instances of times. What one can know are the time intervals in which certain band of frequencies exist, which is a resolution problem.

FT there is no resolution problem in the frequency domain, i.e., we know exactly what frequencies exist; similarly we there is no time resolution problem in the time domain, since we know the value of the signal at every instant of time. Conversely, the time resolution in the FT, and the frequency resolution in the time domain are zero, since we have no information about them. What gives the perfect frequency resolution in the FT is the fact that the window used in the FT is its kernel, the e^{jwt} function, which lasts at all times from minus infinity to plus infinity. Now, in STFT, our window is of finite length, thus it covers only a portion of the signal, which causes the frequency resolution to get poorer.

What is meant by getting poorer is that, we no longer know the exact frequency components that exist in the signal, but we only know a band of frequencies that exist. In FT, the kernel function, allows us to obtain perfect frequency resolution, because the kernel itself is a window of infinite length. In STFT is window is of finite length, and we no longer have perfect frequency resolution.

If we make length of the window in the STFT infinite, just like as it is in the FT, to get perfect frequency resolution than we loose all the time information, you basically end up with the FT instead of STFT.

If we use a window of infinite length, we get the FT, which gives perfect frequency resolution, but no time information. Furthermore, in order to obtain the stationarity, we have to have a short enough window, in which the signal is stationary. The narrower we make the window, the better the time resolution, and better the

assumption of stationarity, but poorer the frequency resolution. The Wavelet transform (WT) solves the dilemma of resolution to a certain extent.

3.6 Wavelet Transform (Multiresolution Analysis)

The time and frequency resolution problems are results of a physical phenomenon (the Heisenberg uncertainty principle) and exist regardless of the transform used, it is possible to analyze any signal by using an alternative approach called the *multiresolution analysis (MRA).*

MRA, as implied by its name, analyzes the signal at different frequencies with different resolutions. Every spectral component is not resolved equally as was the case in the STFT.

MRA is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies.

This approach makes sense especially when the signal at hand has high frequency components for short durations and low frequency components for long durations. Fortunately, the signals that are encountered in practical applications are often of this type.

3.7 Sampling and the Discrete Wavelet Series

In order for the Wavelet transforms to be calculated using computers the data must be discretized. A continuous signal can be sampled so that a value is recorded after a discrete time interval, if the Nyquist sampling rate is used then no information should be lost. With Fourier Transforms and STFT's the sampling rate is uniform but with wavelets the sampling rate can be changed when the scale changes. Higher scales will have a smaller sampling rate. According to Nyquist Sampling theory, the new sampling rate N2 can be calculated from the original rate N1 using the following:

$$N_2 = \frac{S_1}{S_2} N_1 \qquad (3.4)$$

Where, S_1 and S_2 are the scales. So every scale has a different sampling rate.

After sampling the Discrete Wavelet Series can be used, however this can still be very slow to compute. The reason is that the information calculated by the wavelet series is still highly redundant, which requires a large amount of computation time. To reduce computation a different strategy known as Discrete Wavelet Transform (DWT) method is used.

3.8 DWT

The DWT provides sufficient information for the analysis and synthesis of a signal, but is advantageously, much more efficient. Discrete wavelet analysis is computed using the concept of filter banks. Filters of different cut-off frequencies analyze the signal at different scales. Resolution is changed by the filtering, the scale is changed by upsampling and downsampling. If a signal is put through two filters:

(i) A high-pass filter, high frequency information is kept, low frequency information is lost.

(ii) A low pass filter, low frequency information is kept, high frequency information is lost.

Then the signal is effectively decomposed into two parts, a detailed part (high frequency), and an approximation part (low frequency). The subsignal produced from the low filter will have a highest frequency equal to half that of the original. According to Nyquist sampling this change in frequency range means that only half of the original samples need to be kept in order to perfectly reconstruct the signal. More specifically this means that upsampling can be used to remove every second sample. The scale has now been doubled. The resolution has also been changed, the filtering made the frequency resolution better, but reduced the time resolution.

The approximation subsignal can then be put through a filter bank, and this is repeated until the required level of decomposition has been reached. The ideas are shown in *Fig-3.2.*

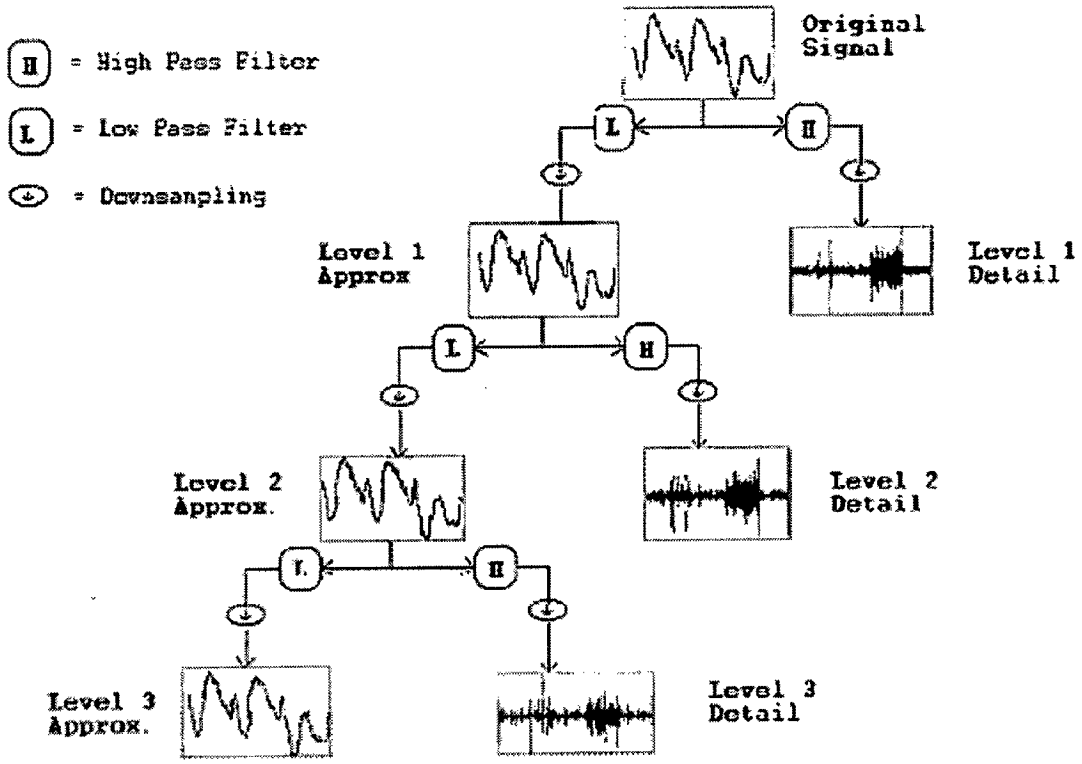


Fig-3.2- 1-D decomposition using DWT

The DWT is obtained by collecting together the coefficients of the final approximation subsignal and all the detail subsignals.

3.9 -2 D Wavelet Analysis

Images are treated as two dimensional signals, they change horizontally and vertically, thus 2D wavelet analysis must be used for images. 2D wavelet analysis uses the same *mother wavelets* but requires an extra step at every level of decomposition.

The 1D analysis filtered out the high frequency information from the low frequency information at every level of decomposition; so only two sub signals were produced at each level. In 2D, the images are considered to be matrices with N rows and M columns.

At every level of decomposition the horizontal data is filtered, then the approximation and details produced from this are filtered on columns. 2-D decomposition using DWT is described in *Fig-3.3* below-

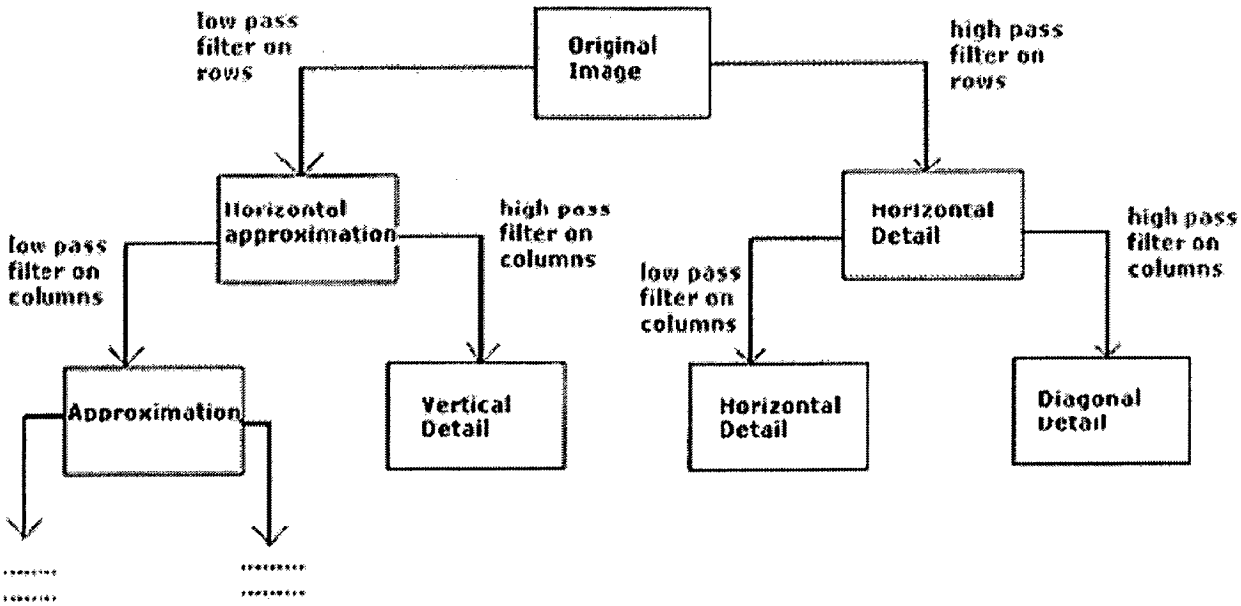


Fig-3.3- 2-D decomposition using DWT

At every level, four sub-images are obtained; the approximation, the vertical detail, the horizontal detail and the diagonal detail. The wavelet analysis has found how the image changes vertically, horizontally and diagonally.

Fig-3.4 below gives the 2D decomposition structure of mammogram image.

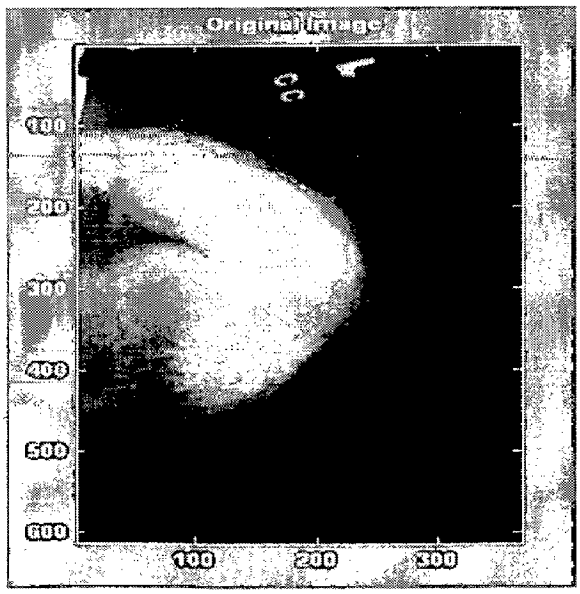
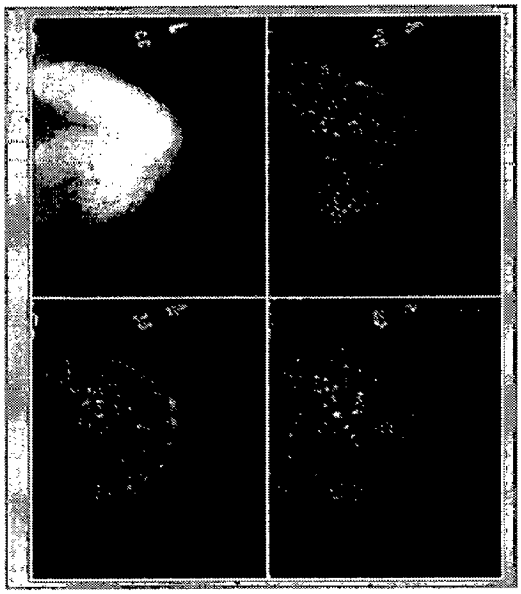
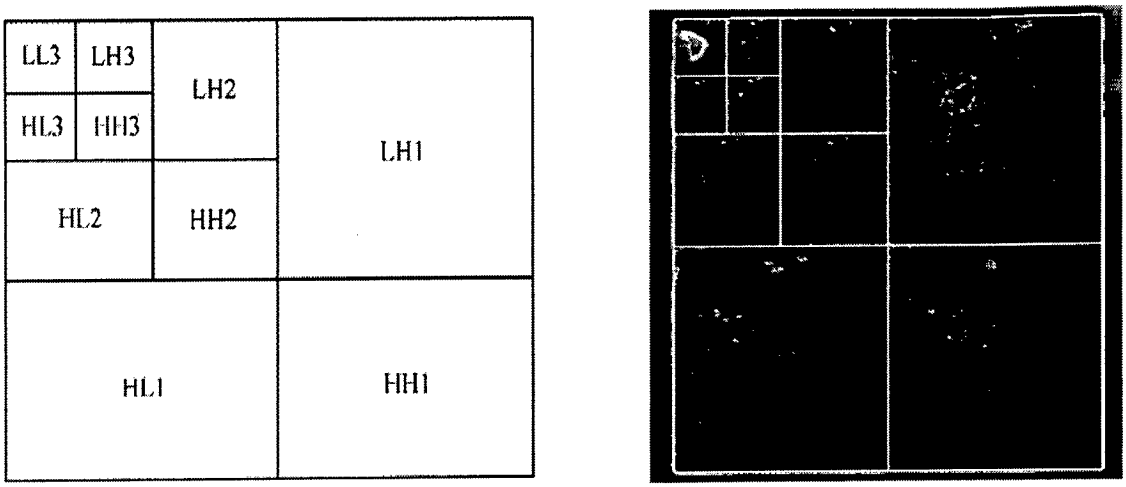


Fig-3.4- (a)original Image



(b) Decomposition at level one

Fig-3.5- below shows the 3-level 2-D wavelet transform.



(a) (b)

Fig-3.5- (a) 3-level 2-D wavelet transform (b) Mammogram image decomposition at level 3

Wavelets hold great promise as an integral part of the unified solution to several problems in medical imaging, and in particular mammography, in the areas of: data compression, microcalcification detection, contrast enhancement and microcalcification segmentation.

Chapter 4

WAVELETS APPLIED TO MAMMOGRAMS

Introduction- In this chapter a wavelet based sub-band filtering method is applied to enhance the mass and calcification shown in digital mammograms by inhibiting noise. Combined enhancement measure also known as D-Index [29] explained in chapter 6 is measured to evaluate the performance of enhancement algorithm.

The method is based on sub-band transformation due to its decomposition characteristic and includes two steps: noise inhibition and boundary enhancement. To validate the effectiveness of the proposed technique, both conventional and proposed method have been applied to real mammograms with microcalcifications-from MIAS database [2] and the enhancement performance has been compared. Results in this study demonstrate that the proposed method improves the quality of the image more than the other enhancement methods.

4.1 Statistical Based Sub-Band Filtering Technique

Many digital image enhancement algorithms have been developed and were reviewed in [17]. Of these algorithms, histogram equalization (HISTEQ), contrast limited adaptive histogram equalization (CLAHE), pseudo-coloring(PC) and unsharp masking (UM) are used for comparison with the proposed wavelet based sub-band filtering(WL) technique.

Most of the conventional image enhancement algorithms generally enhance image contrast, but they simultaneously amplify noise and artifacts. In interpreting mammograms, noise and artifacts are undesirable and can potentially lead to false diagnoses.

The superiority of the wavelet transform for enhancing the contrast in digital medical images is well established [18-24]. Similar to other transforms for example, Fourier transform, the wavelet transform decomposes an image into a set of frequency channels.

However, unlike a Fourier transform, which uses constant frequency intervals, the wavelet decompositions are represented at various resolutions, on a logarithmic scale (band-pass sub-band images). This multi-scale representation provides the flexibility to enhance image objects of various sizes and enables noise magnification to be controlled.

Several methods, based on wavelet transformation, have been presented for noise reduction and enhancement by thresholding the wavelet coefficients [21-24]. The fundamental characteristics of these methods are that no spurious oscillations are introduced and the boundary information in the image is preserved.

A block statistic analysis technique is introduced to enhance the contrast of the features in digital mammograms. For each mammogram, a wavelet transform is applied to decompose the image into band-pass sub-band images. For each of the sub-band images, mean and standard deviation values within a block are calculated. In the high frequency sub-bands, the mean value is used for thresholding to inhibit noise amplification.

4.2 Sub-Band Transformation

In recent years, the sub-band transformation has already been broadly applied providing a common framework for numerous practical applications, such as image enhancement, data compression and image denoising [25-28]. The major concept behind the 2-D sub-band transformation is to analyze each image by decomposing the image at various resolutions, using a set of prototype basis functions.

Eventually, the sets of basis functions are biorthogonal low-pass and high-pass impulse responses. Using these filters, images are hierarchically decomposed into multiple levels. Each sub-level of the decomposed information contains one coarse

component and three fine components, obtained originally from the coarse component of the upper-level information.

Each sub-level component related to the sub-band information in an image is normally in a pyramid resolution, which is decreased by a factor of two. The forward 2-D sub-band transformation, which decomposes the upper-level coarse component into one sub-level coarse and three sub-level fine components by filtering the image using low-pass filters and high-pass filters. The sub-level coarse component obtained by low-pass filtering the upper-level coarse component in horizontal and vertical directions. The three sublevel fine components are-

- Obtained by high-pass filtering in the horizontal direction and low-pass filtering in the vertical direction.
- Obtained by high-pass filtering in the vertical direction and low-pass filtering in the horizontal direction.
- Obtained by high-pass filtering in the vertical and horizontal directions.

Fig-4.1 presents the i^{th} decomposition procedure of the 2-D sub-band transformation for the first two levels of the coarse component, $f(x,y;c_i)$ and fine components, $f(x,y;d_{i,j})$,for i>0 and $j=1,2,3$. Each of the four sub-level components follows from the scheme of the forward 2-D sub-band transformation. With respect to the first level information concerning the sub-band decomposition, the image in the upper-left region includes the primary information about the original image, and will be used to decompose the next level to obtain the other four sub-level components in the second level.

The general inverse 2-D sub-band transformation used to reconstruct the images from each sub-level component. In this study, the 2-D decomposition and reconstruction procedures are all based on a set of biorthogonal basis functions, called Perfect Reconstruction Quadrate Mirror Filters (PR-QMF) [25]. The major reason for the use of these biorthogonal basis functions is that their system coefficients are symmetric, and they ensuring that no phase compensation problem affects the sub-band transformation [27-28].

4.3 Statistical Analysis

As mentioned above, the characteristics of the original image can be decomposed using the presented sub-band transformation. Each sub-level coarse image that is processed only by low-pass filters remains primary information, and the other images processed through high-pass filters remain fine components, including the feature of image boundaries and the undesired noise in the original image [26]. These decomposed fine components are modified easily to reduce the image noise without affecting the image boundary information.

Different regions of sub-level fine components yield different statistical values that can be used for separating the undesired noise from the useful features of the image boundary.

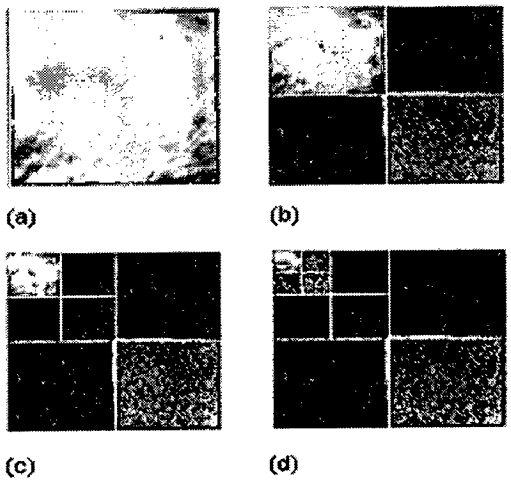


Fig-4.1-The decomposition structure shown as the procedure of 3rd level sub-band transformation.

Practically, the core procedure of the image denoising method is to determine the sub-band threshold values measured from individual sub-level fine components. Decomposed information pertaining to each sub-level fine component normally takes both positive and negative values, and most of the noise information always concerns to the positive and negative values near zero, the boundary information will be retained in the sub-level fine components that present larger absolute values.

A bi-level thresholding method is designed to separate the noise and boundary components. The positive threshold, $Thresd_{i,j}+$, and the negative threshold,

$Thresd_{i,j}$ – are determined for each sub-level fine component as,

$$Threshd_{i,j}+ = \frac{1}{N_+}\sum_{k=1}^{k=N_+} f(x,y;d_{i,j})_+$$

$$Threshd_{i,j}- = \frac{1}{N_-}\sum_{k=1}^{k=N_-} f(x,y;d_{i,j})_-$$

where, $Thresd_{i,j}+$ is the mean value determined from all positive values in each sub-level fine component, $f(x,y;d_{i,j}+)$,for $j=1,2,3$, and $Thresd_{i,j}-$ is the mean value of the negative parts, computed just like $Thresd_{i,j}+$, N+ and N-represent the numbers of positive $f(x,y;d_{i,j}+)$ and negative $f(x,y;d_{i,j}-)$ values in each region.

The sub-level-dependent thresholds are applied to modify the decomposed sub-level fine component as follows.

$$If\ (f\ (x,y;d_{i,j}) < Thresd_{i,j-}\ or\ f\ (x,y;d_{i,j}) < Thresd_{i,j+})$$

$$then\ f_{new}(x,y;d_{i,j}) = f(x,y;d_{i,j})$$

$$else\quad f_{new}(x,y;d_{i,j}) = 0$$

where, $f_{new}(x,y;d_{i,j})$ are the new sub-level fine components. Empirically, the components, which are determined to be within the bi-level threshold are assigned a zero value because, they belong to the noise information in the original image.

4.4 Results

In this study, ten digital mammograms randomly selected from MIAS[2] mini-mammographic database were used to justify the effectiveness of the proposed technique.

About MIAS Mini-mammographic database-For analyzing the microcalcifications the image resolution needs to be very high. The image size in mini-mammographic database has been clipped and padded to become 1,024*1,024 pixels. The dynamic range of the pixel is eight bit- that is, a gray scale of 0 to 255. Background tissues included in this database include fatty, fatty glandular, and dense glandular. The database yields abnormalities such as calcification, well defined circumscribed masses, masses with specules, ill defined masses, architectural distortion, asymmetry and normal.

The ground truth of each mammogram is also included in the database, which provides the location where the abnormality is situated in terms of *(x, y, r)* within a given mammogram, where, *(x, y)* are the *x* and *y* axis coordinates, and r is the approximate radius of the circle enclosing the abnormality [2].

A cropping operation is applied to the image to prune the images with the help of crop operation in image processing. Cropping cuts of the unwanted portions of the image, thus all the unnecessary background information and most of noise are eliminated by clipping large number of background pixels from the images.

After, the ROI has been extracted, its is processed by different enhancement algorithms like - histogram equalization (HISTEQ), contrast limited adaptive histogram equalization (CLAHE), pseudo-coloring(PC) ,unsharp masking(UM) and statistical based sub-band filtering technique (WL) , to evaluate objectively the improvement in contrast.

The performance of the sub-band based enhancement technique is verified by obtaining a quantitative contrast value, called the D-index [29] to evaluate the effectiveness of the image enhancement. The smaller is the value of D-index the better is the enhancement.

Fig-4.2, 4.3 and 4.4 below shows the results of mammogram images with real microcalcifications processed by different enhancement techniques.

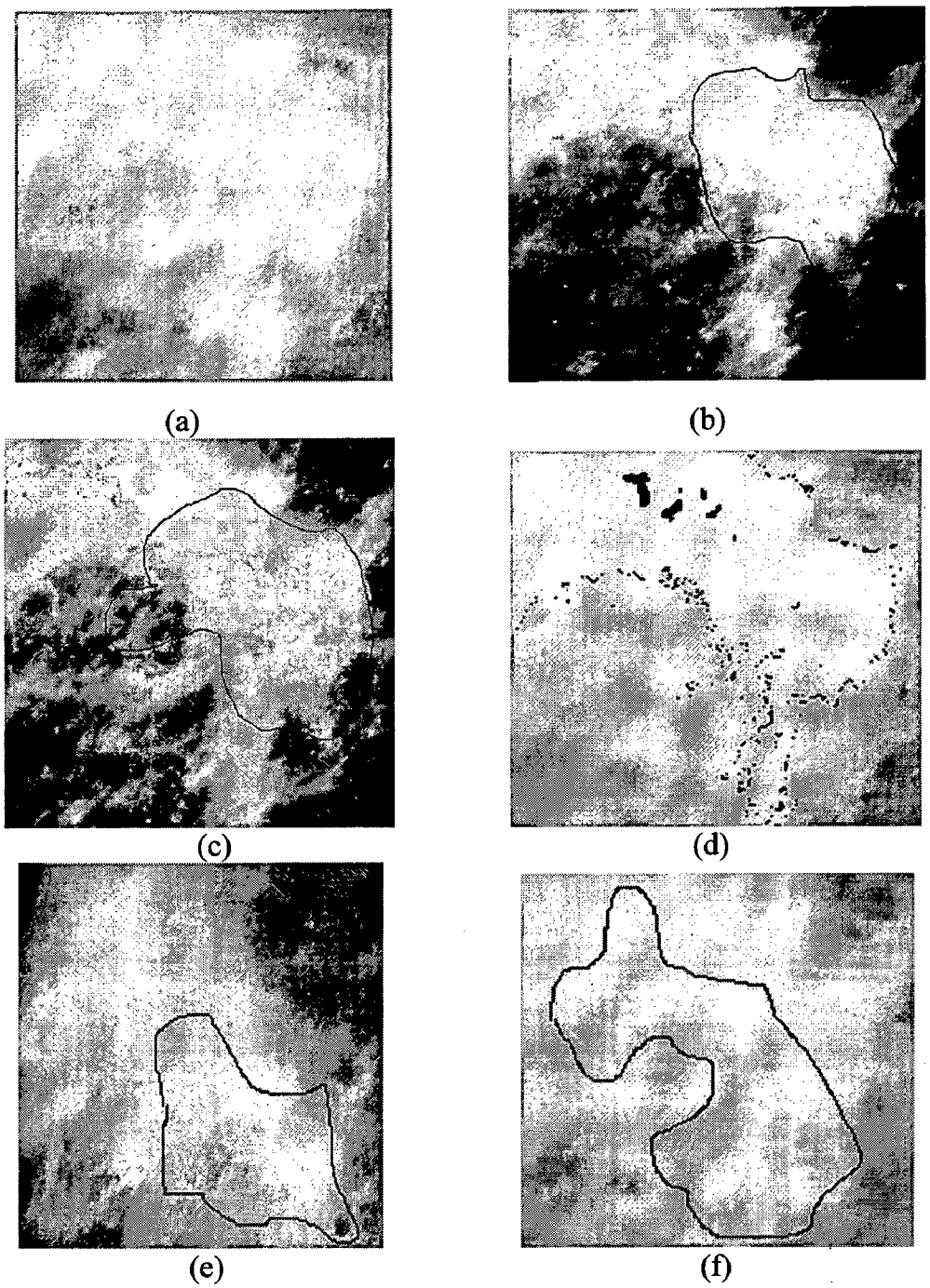


Fig-4.2- The results of mammogram image (mdb209)[2] with real microcalcifications processed by different enhancement techniques.(a) original mammogram; (b) histogram equalization processed; (c) CLAHE processed; (d) pseudo-color processed; (e) unsharp masking processed and (f) statistical-based sub-band filtering enhancement processed.

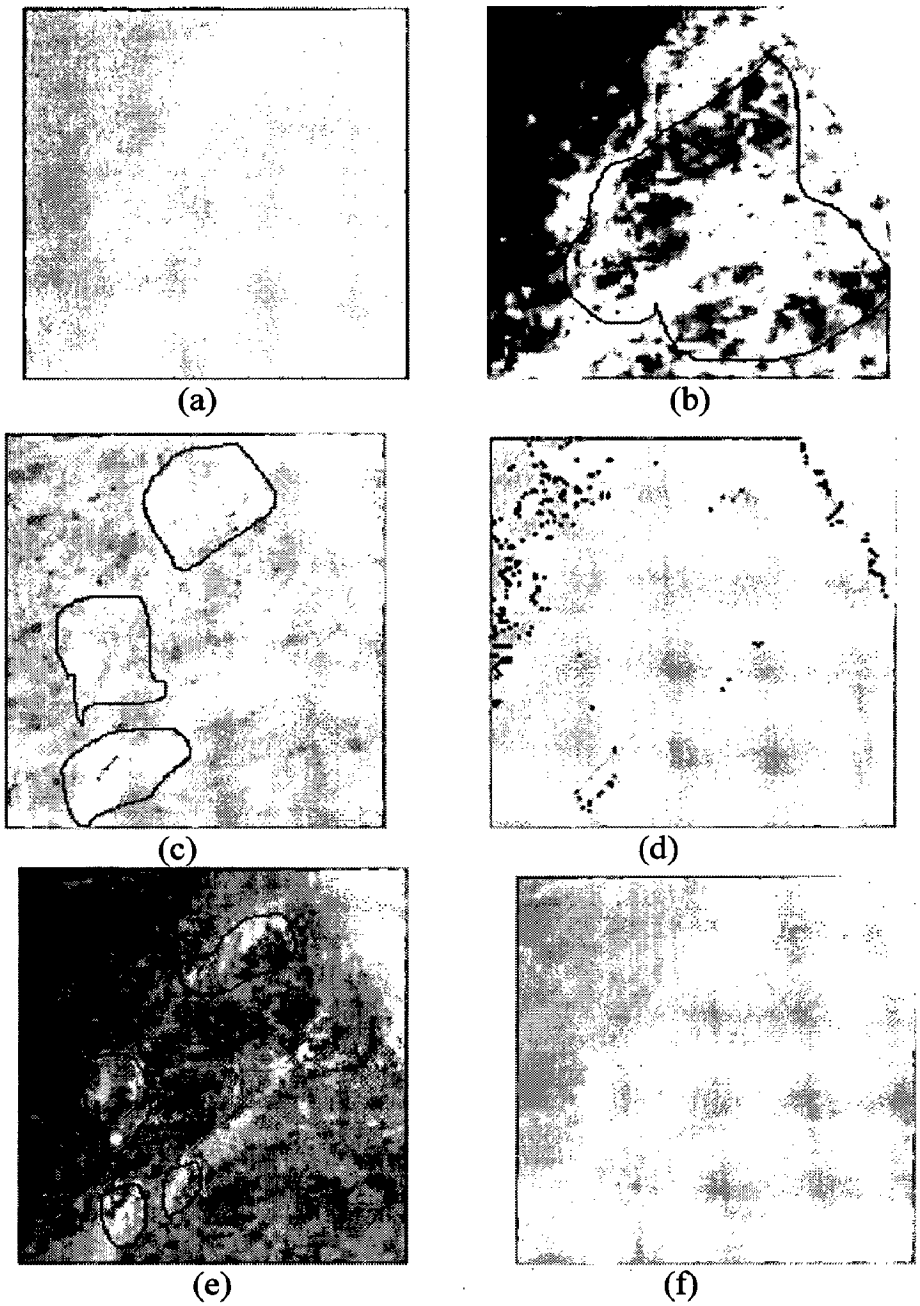


Fig-4.3- The results of mammogram image (mdb249)[2] with real microcalcifications processed by different enhancement techniques.(a) original mammogram; (b) histogram equalization processed; (c) CLAHE processed; (d) pseudo-color processed; (e) unsharp masking processed and (f) statistical-based sub-band filtering enhancement processed.

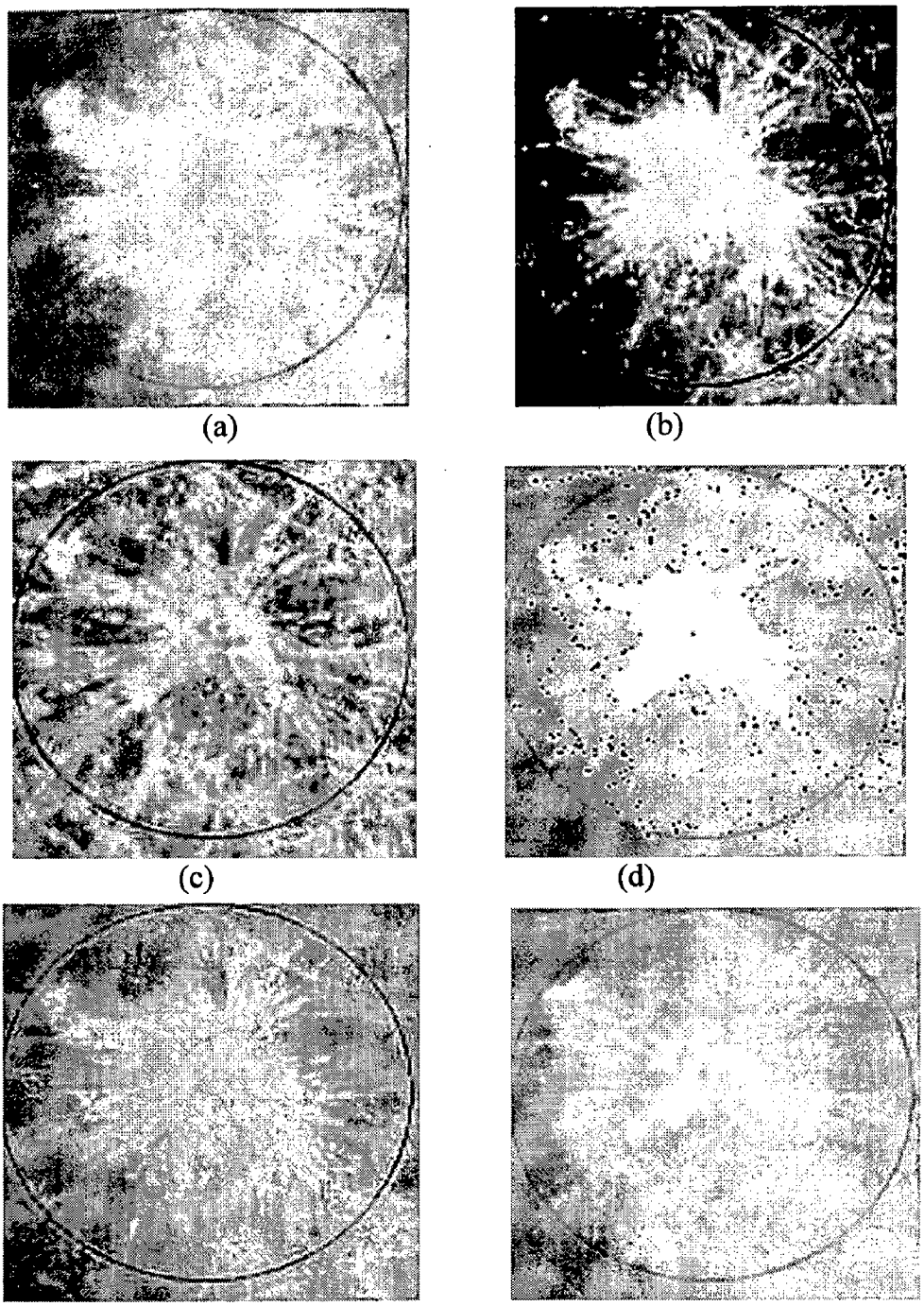


Fig-4.4- The results of mammogram image (case19-Mc-Gill database)[41] with real microcalcifications processed by different enhancement techniques.(a) original mammogram; (b) histogram equalization processed; (c) CLAHE processed; (d) pseudo-color processed; (e) unsharp masking processed and (f) statistical-based sub-band filtering enhancement processed.

D Index comparison chart for different enhancement techniques is given in *Table-4.1* below.

File Name	D Index [29]				
	HISTEQ	CLAHE	PC	UM	WL
mdb209	22.53	1.81	1.85	1.6472	1.72
mdb213	8.752	2.29	1.97	1.8253	1.78
mdb214	26.68	1.43	1.88	1.8039	1.73
mdb218	10.03	5.71	1.97	4.1257	1.8
mdb219	25.47	1.41	2.15	1.73	1.6398
mdb222	12.86	2.02	1.87	10.9084	1.71
mdb223	17.65	15.2	1.98	1.6678	1.75
mdb226	26.65	11.4	1.92	1.92	1.6197
mdb227	34.48	4.69	1.86	1.84	1.7323

(All the above images were taken from MIAS database [2], enhancement applied on ROI)
Table 4.1 D-Index comparison chart for different enhancement techniques

4.5 Discussion

The differences between the results of enhancement and the methodologies presented in this study are discussed. Traditional histogram equalization (HISTEQ) is less effective as the contrast characteristics for both the desired region (ROI) and the undesired region are enhanced so noise is also enhanced along with microcalcifications and therefore the processed image is distorted. The sub-band transformation removes noise from the image and retain the desired features of the images thereby overcoming the problems of traditional methods. Thus, the statistical-based sub-band enhancement method presented here not only emphasizes the image detail but also retains the important image information without any loss of diagnostic information.

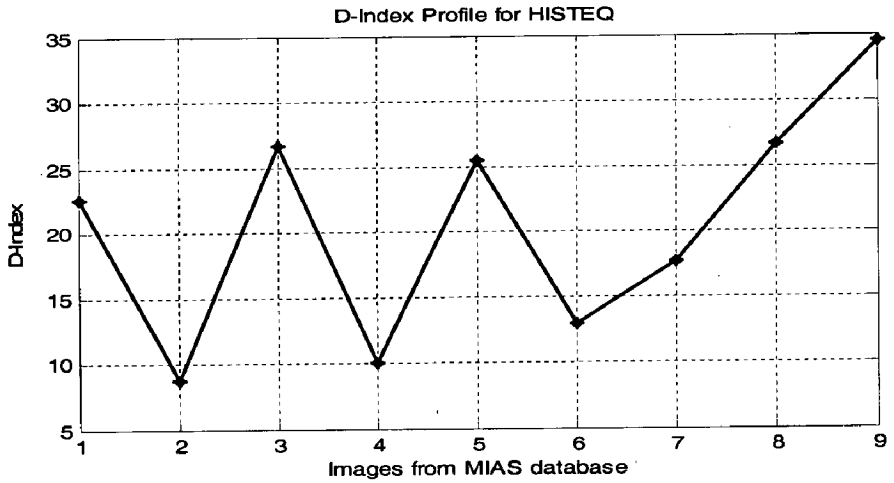
The methodology behind calculation of D-Index is given later in chapter 6. D-Index is the only quantitative measure given in the literature, which uses both standard deviation and entropy in the images to evaluate the performance of the enhancement algorithm. The lesser the value of D-index the better is the enhancement [29].

The *Table-4.2* below shows the maximum and minimum values of the D-index obtained by different image enhancement algorithms applied on nine different images from MIAS database-

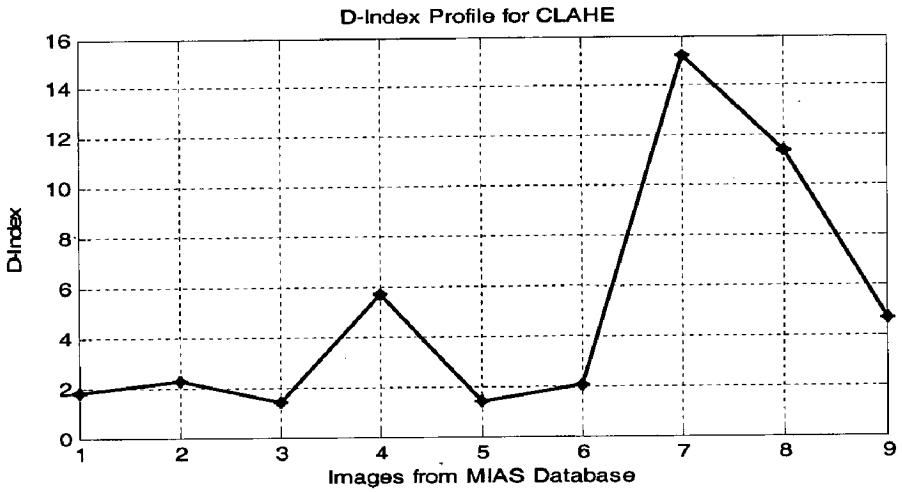
Enhancement Method	Image with Maximum D-index	D-index (Maximum)	Image with Minimum D-index	D-index (Minimum)
HISTEQ	mdb227	34.48	mdb213	8.752
CLAHE	mdb226	11.4	mdb219	1.41
PC	mdb219	2.15	mdb209	1.85
UM	mdb222	10.9084	mdb209	1.6472
WL	mdb226	1.8	mdb218	1.6197

Table-4.2-Range of variation of D-index values for different images

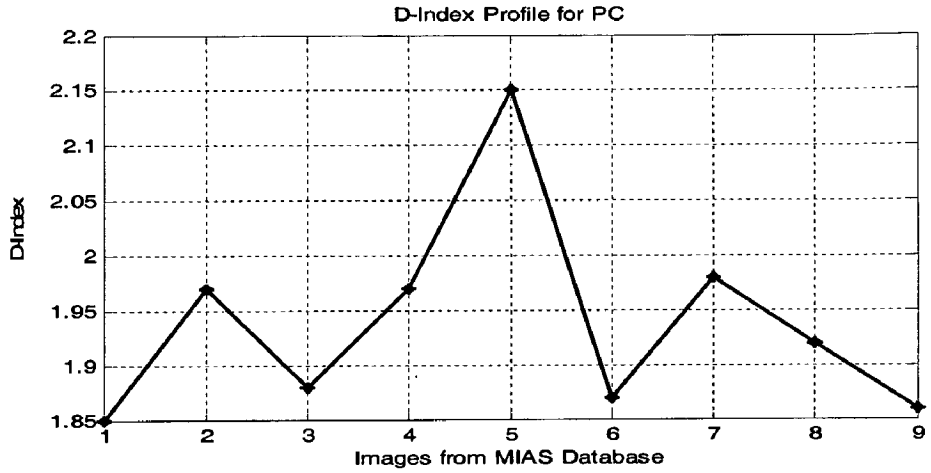
The results shown in table 4.1 are shown below graphically in *Fig-4.5*



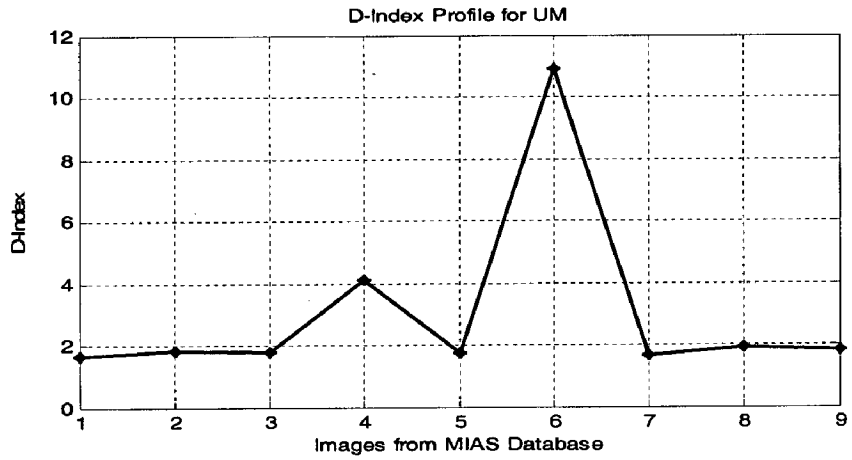
(a)



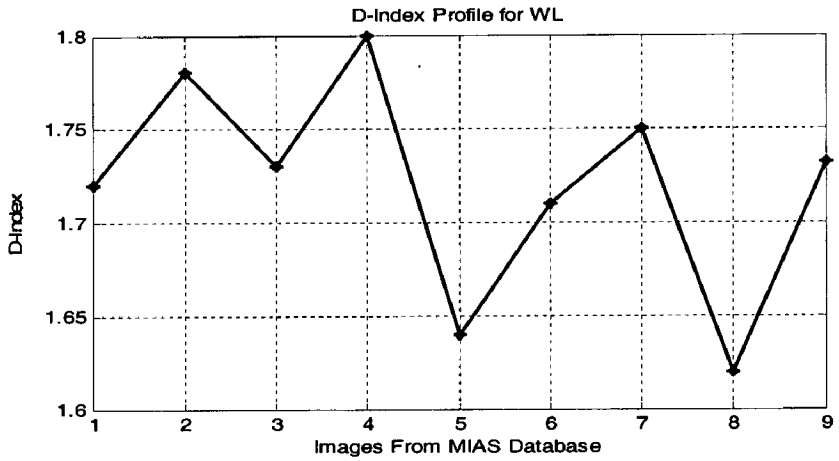
(b)



(c)



(d)



(e)

Fig-4.5- D-Index profile for different enhancement methods as applied to some ROI's of digital mammograms obtained from MIAS database [2]-(a)HISTEQ(b)CLAHE (c)PC (d) UM and(ed)WL.

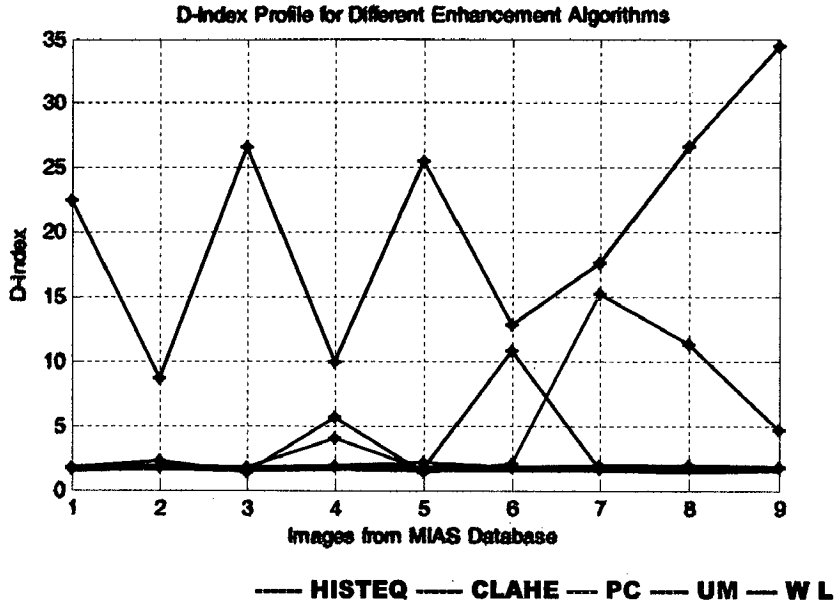


Fig-4.6- D-Index profile for different enhancement methods as applied to some ROI's of digital mammograms obtained from MIAS database [2].

From *Fig-4.6,* it can be visualized that the wavelet based sub-band filtering technique is giving the lowest value for D-index and hence it is best suited for mammogram image enhancement. However, it can be observed that pseudo coloring here is gives the comparable results is just a matter of chance ,because in pseudo-coloring we are doing intensity slicing manually based on histogram characteristics.

This study measures the D index of processed results to elucidate the enhancement of an image. In this simulation, it is found that the statistical-based sub-band enhancement technique can be used to enhance clinically acquired digital mammograms without distortion and can therefore provide more detailed image information.

The promising results of this work suggest that the proposed technique can be routinely used and the proposed method extended to computer-assisted diagnosis of breast diseases in a clinical environment.

Chapter 5

CONTRAST ENHANCEMENT TECHNIQUES

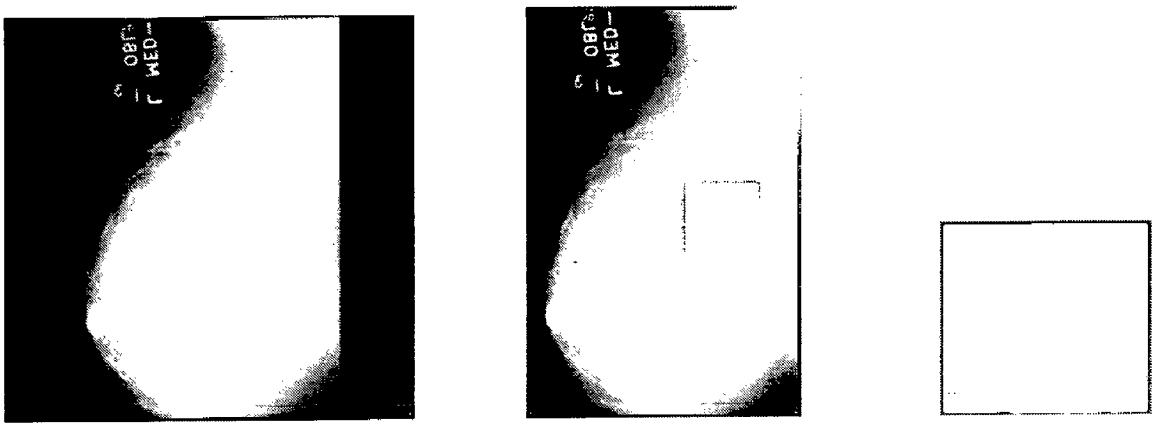
Introduction- **Contrast enhancement is one of the most important issues in image processing. We can obtain more information from the enhanced image, which will be more useful for further processing.**

In mammography, early detection of breast cancer relies upon the ability to distinguish between malignant and benign mammographic features. The detection of small malignancies and subtle lesions is often difficult. In this chapter, various techniques used for mammogram enhancement and their performance is presented. Finally, the use of combination of two enhancement techniques like, unsharp masking and contrast stretching and morphological enhancement and contrast stretching is also proposed.

5.1 Preprocessing: Breast Region Segmentation

The high-resolution mammogram images used in this study are of 1024x1024 pixels and almost 50% of the whole image comprised of background with a lot of noise. In this phase, a cropping operation is applied to the image to prune the images with the help of crop operation in image processing.

Cropping cuts of the unwanted portions of the image, thus all the unnecessary background information and most of noise are eliminated. An example of the cropping that eliminates the unwanted black background is given in *Fig-5.1*. By clipping large number of background pixels from the images, storage requirements, I/O time, and image processing time is significantly reduced.



(a) (b) (c)

Fig- 5.1- Preprocessing of a mammogram from MIAS [2] (mdb231): (a) Original Image (b) Cropped image with ROI marked, and (c) ROI image.

5.2 Contrast Enhancement in Digital Mammography

In mammography, early detection of breast cancer relies upon the ability to distinguish between malignant and benign mammographic features. The detection of small malignancies and subtle lesions is often difficult.

Contrast enhancement can make more obvious, unseen or barely seen features of a mammogram without requiring additional radiation [3]. Mainly, image enhancement includes intensity and contrast manipulation, noise reduction, background removal, edges sharpening, filtering, etc. The task of mammogram enhancement is to sharpen the edges or boundaries of ROIs, or to increase the contrast between ROIs and background [3].

It is well-known that if a region differs in luminance from its surroundings by less than 2%, it is indistinguishable to human eye [1]. Although microcalcifications usually are brighter than their surroundings, the contrast for some microcalcifications in a dense breast is quite low and human eyes can hardly distinguish them. The aim of contrast enhancement is to increase the contrast of microcalcifications over this threshold.

In this section, various techniques used for mammogram enhancement and their performance is presented.

The notion of contrast can be approximately defined as the relative difference in intensity between an image structure and its background. The principal objective of contrast enhancement or sharpening is to emphasize fine detail in a mammogram, or to enhance detail that is blurred.

The contrast enhancement methods can be categorized as indirect and direct approaches. Indirect approaches, mainly, modify the histograms without defining the contrast. Direct approaches define the contrast first, and then enhance the contrast based on the defined measurements.

Enhancement of mammograms is a delicate process, which involves improving contrast while preserving visual acuity. Too little enhancement may preclude the detection of minor microcalcification peaks, while too much enhancement may significantly increase the amplitude of background noise leading to a large number of false detections.

5.2.1 Complexities of Microcalcifications Enhancement

Many factors contribute to difficulties in detecting microcalcifications. Firstly, microcalcifications are small, and exhibit a broad range of variability with respect to their morphology, size, and distribution pattern. Secondly, microcalcifications are often situated in a non-homogeneous background, and due to their low contrast with the background, their intensity may be similar to noise or other structures (e.g. film artifacts). If the background region is composed of fatty tissue the process of identifying microcalcifications is easier than if they are embedded in dense fibro glandular tissue.

5.2.2 Contrast Stretching

The simplest method of increasing the contrast in a mammogram is to adjust the histogram so that there is a greater separation between foreground and background [7]. *Fig- 5.2* below shows the transformation used for contrast stretching.

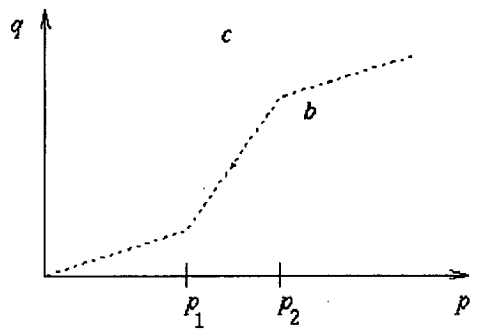


Fig-5.2- Contrast enhancement (between p1 and p2)

The result of applying contrast stretching operation on a mammogram image is depicted below in *Fig-5.3*.

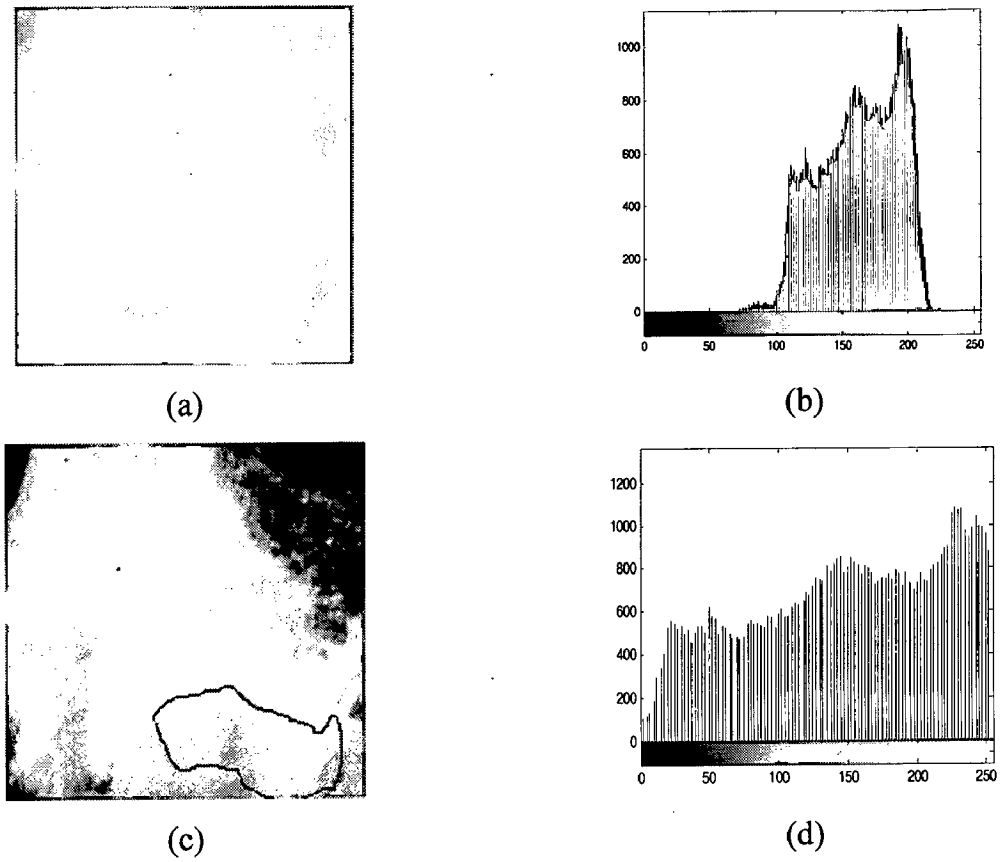


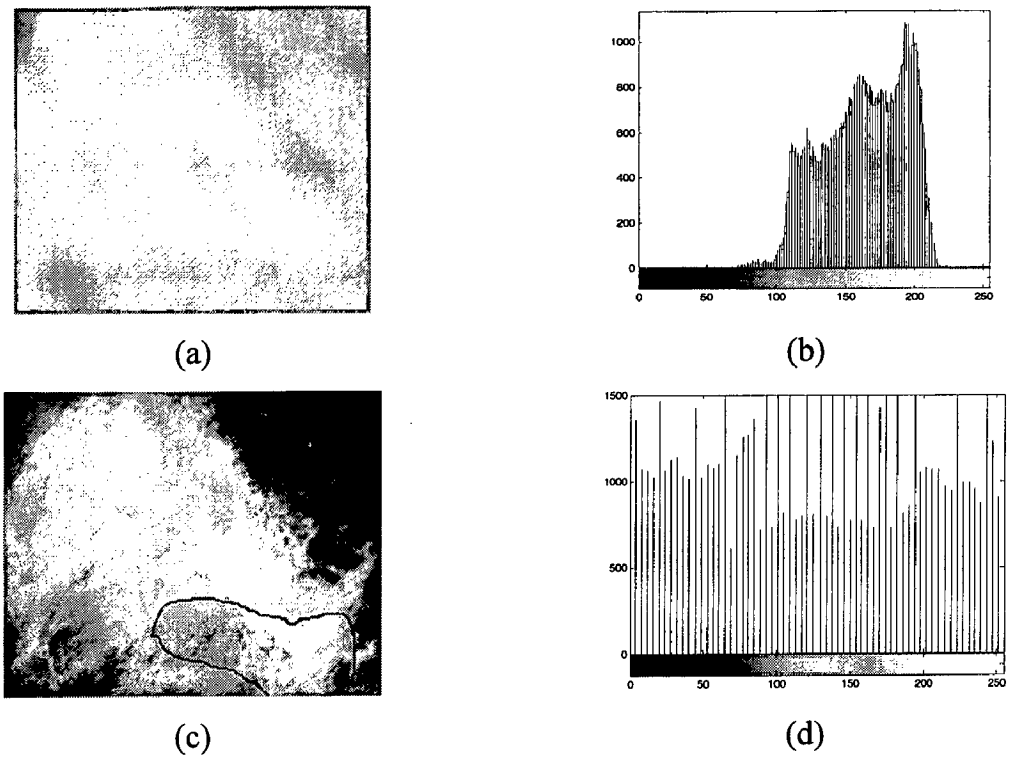
Fig-5.3- ROI Image from MIAS [2] (mdb209): (a) Original ROI Image (b) Original ROI Image Histogram (c) Enhanced ROI image and (d) Enhanced ROI Image Histogram.

Histogram is a plot between gray level intensity and gray level frequency. As seen in Fig. 5.3 by applying CS algorithm the histogram is stretched over the entire gray scale.

5.2.3 Histogram Equalization (HISTEQ)

Histogram equalization (HISTEQ) method is a well-known gray scale manipulation technique. In histogram equalization, the goal is to map the input image to the output image so that gray values in the output image are uniformly distributed. For most practical images, gray values need to be redistributed. In histogram equalization we try to spread gray values uniformly over the full gray-scale range. It increases the contrast range in an image by increasing the dynamic range of gray levels [31].

The result of applying histogram equalization (HISTEQ) algorithm on mammogram image is depicted below in *Fig-5.4*.



(a) (b)

(c) (d)

Fig-5.4- ROI Image from MIAS [2] (mdb209): (a) Original ROI Image (b) Original ROI Image Histogram (c) Enhanced ROI image and (d) Enhanced ROI Image Histogram.

As seen in Fig. 54 by applying HISTEQ algorithm the histogram is flattened over the entire gray scale.

Another variation of conventional histogram equalization is Contrast-Limited Adaptive Histogram Equalization (CLAHE) algorithm [31].

5.2.4 Contrast Limited Adaptive Histogram Equalization (CLAHE)

Contrast-limited adaptive histogram equalization operates on small data regions (tiles) rather than the entire image. Each tile's contrast is enhanced so that the histogram of each output region approximately matches the specified histogram (uniform distribution by default).

The contrast enhancement can be limited in order to avoid amplifying the noise, which might be present in the image. The histogram filter performs a so-called contrast limited adaptive histogram equalization (CLAHE) on the data set. The CLAHE algorithm partitions the images into contextual regions and applies the histogram equalization to each one. This evens out the distribution of used grey values and thus makes hidden features of the image more visible.

The result of applying contrast limited adaptive histogram equalization (CLAHE) algorithm on mammogram image is depicted below in *Fig-5.5*.

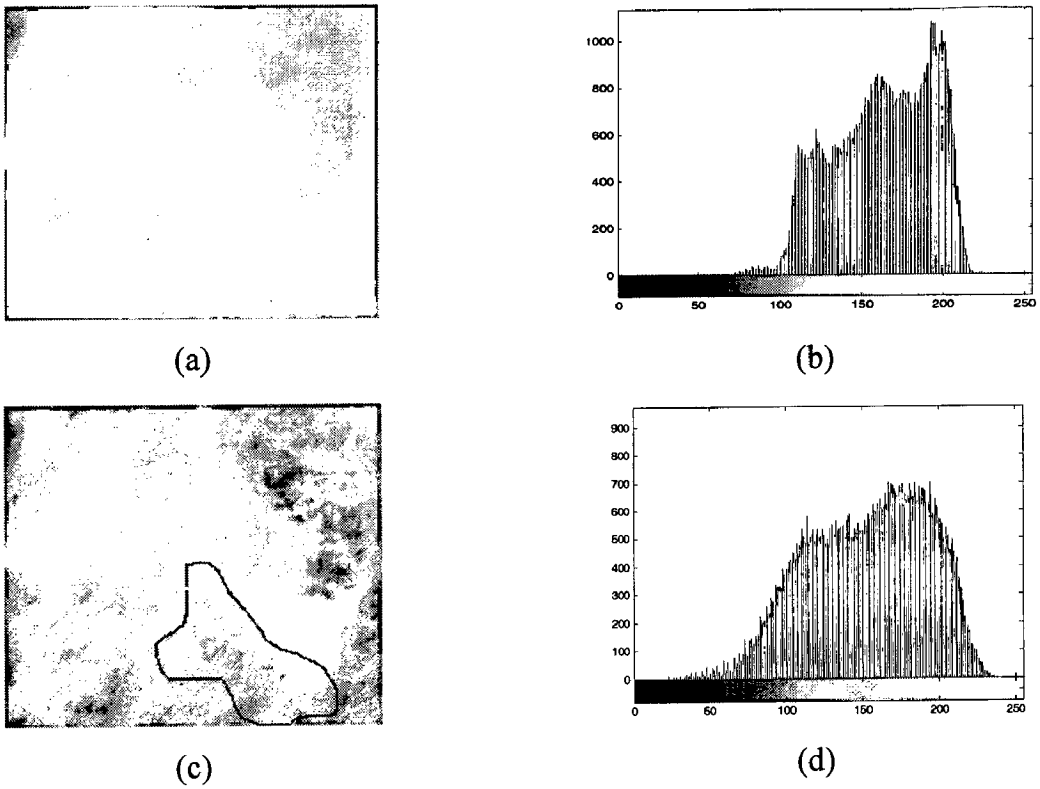


Fig-5.5- ROI image from MIAS [2] (mdb209): (a) Original ROI image (b) Original ROI image histogram (c) Enhanced ROI image and (d) Enhanced ROI image histogram.

As seen in Fig- 5.5 by applying CLAHE algorithm there is a smooth transition of gray-level profile.

5.2.5 Enhancement by Difference Image Technique

In this method image enhancement is achieved by taking the difference of the original image by the low pass filtered image. The mask used low pass filtering is as shown in *Fig-5.6* below-

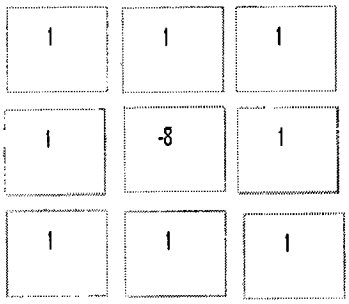


Fig-5.6-3×3 mask used for low pass filtering

The result of applying difference image technique on mammogram image is depicted below in *Fig-5.7.*

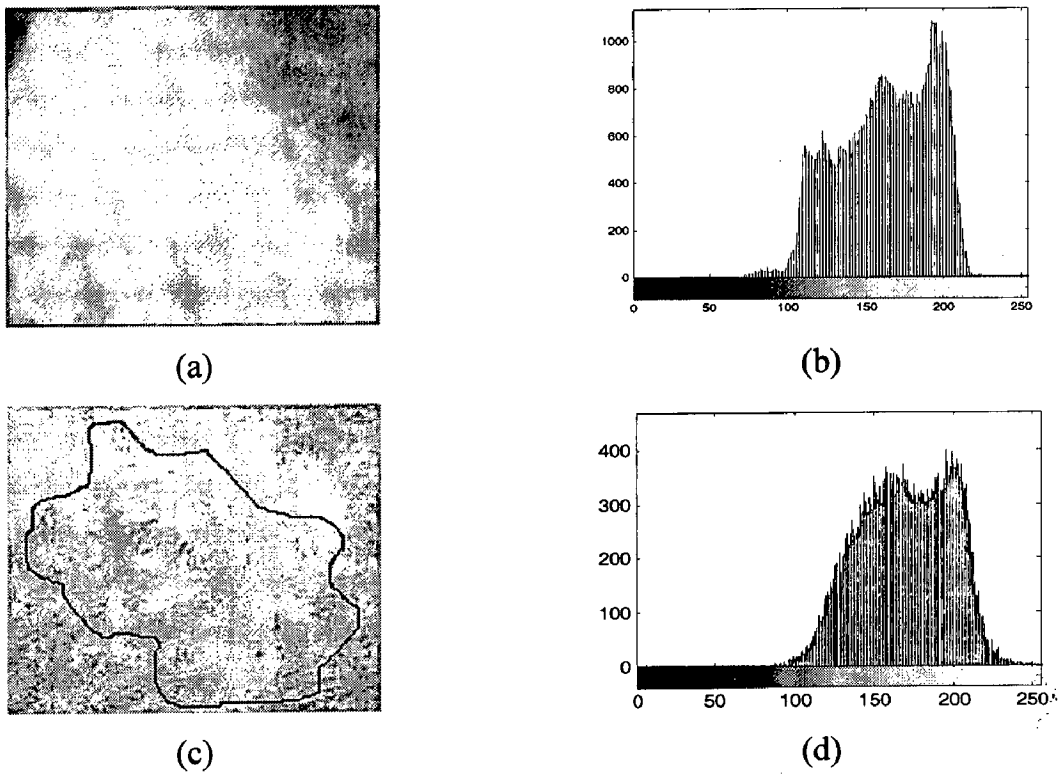


Fig-5.7- ROI image from MIAS [2] (mdb209): (a) Original ROI image (b) Original ROI image histogram (c) Enhanced ROI image and (d) Enhanced ROI image histogram.(difference image technique)

5.2.5 Convolution Mask Enhancement (CME)-Unsharp Masking

The unsharp mask operation actually consists of performing several operations in series on the original image. Those operations, in order, are:

- Blur the original.
- Subtract the blurred image from the original (the resulting difference image is called the "mask") .
- Add the mask to the original.

The resulting image (original plus mask) will appear "sharper" to our eye. The ability of detection of microcalcifications in the digital mammograms was improved by unsharp-mask filtering. The resulting print is sharper because low-frequency information in the image is reduced in intensity while high frequency details are amplified [31].

The digital unsharp masking approximates the process of using a 3*3 unsharp mask. An example of such a 3*3 unsharp mask is shown in *Fig-5.8* below-

-0.125	-0.125	-0.125
-0.125	2	-0.125
-0.125	-0.125	-0.125

Fig-5.8-3×3 unsharp mask

The result of applying convolution mask enhancement (CME) on mammogram image is depicted below in *Fig-5.9.*

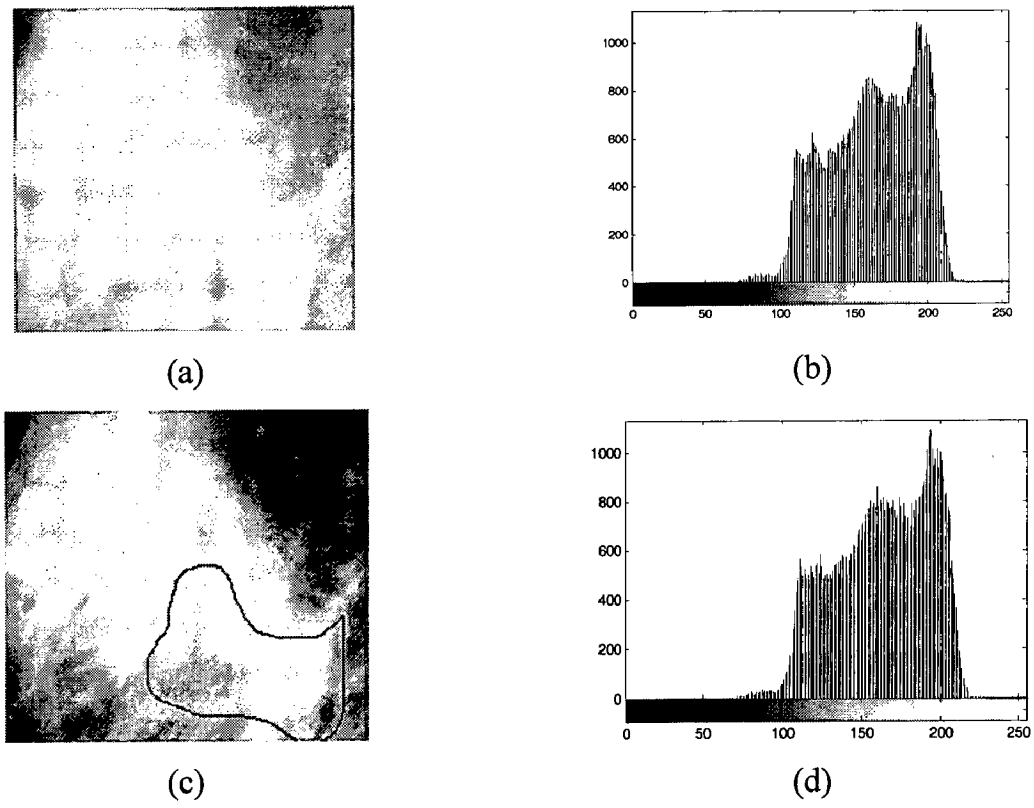


Fig-5.9- ROI image from MIAS [2] (mdb209): (a) Original ROI image (b) Original ROI image histogram (c) Enhanced ROI image and (d) Enhanced ROI image histogram.

5.2.6 Pseudo-Coloring of Mammograms

Pseudo-color (also called false color) image processing consists of assigning colors to gray values based on a specific criterion. The term pseudo or false color is

used to differentiate the process of assigning colors to monochrome images from the processes associated with true color images.

The principal use of pseudo color is for human visualization and interpretation of gray-scale events in an image. One of the principal motivations for using color is the fact that humans can discern thousands of color shades and intensities, compared to only two dozen or so shades of gray.

Medical image is usually obtained in noisy environment and it is normally corrupted by noise. This makes the tissues important to diagnosis very fuzzy and difficult to observe even by trained eyes.

Pseudo coloring is an image enhancement technique, which helps physicians to isolate relevant tissues and groups different tissues together. According to the mapping function, any input gray level is assigned one of the two colors, depending on whether it is above or below the value of l_i.

When more levels are used the mapping function takes a staircase form as shown below in *Fig-5.10.*

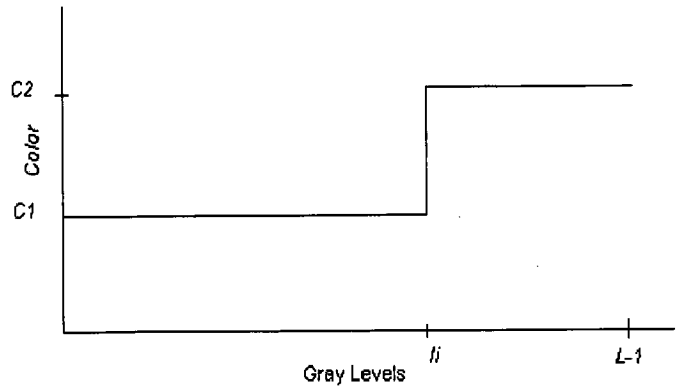


Fig-5.10- A representation of intensity-scaling technique

The result of applying pseudo-coloring algorithm on mammogram image is depicted below in *Fig-5.11.*

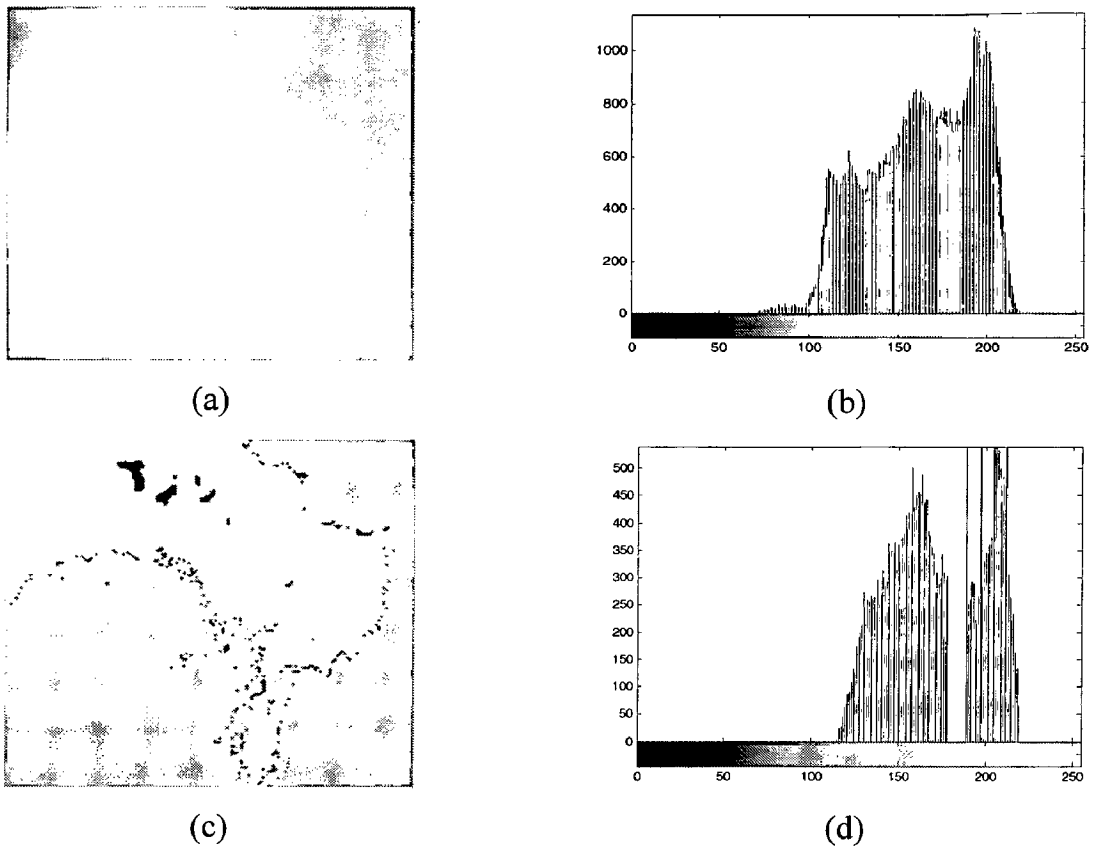


Fig-5.11- ROI Image from MIAS [2] (mdb209): (a) Original ROI image (b) Original ROI image histogram (c) Enhanced ROI image and (d) Enhanced ROI image histogram.

As seen in Fig. 5.11 by Appling PC algorithm pixels having gray level intensity between 180-215 are colored in blue.

5.2.7 Morphological Enhancement

Morphological contrast enhancement is based on the notion of morphological top-hats which were first proposed by Meyer [45]. A top-hat is a residual filter which preserves those features in an image that can fit inside the structuring element (SE) and removes those that cannot.

The top-hat transform is used to segment objects that differ in brightness form the surrounding background in the images with uneven background intensity. A more detailed description on top-hat can be found in [45].

Morphological contrast enhancement is derived by calculating the dual area top-hats in parallel.

The high-intensity regions, i.e. features that cannot accommodate the structuring element are removed from an image by performing a structural opening. The top-hat by opening, TH_O, is defined as the difference between the original image, *OI*, and its grayscale opening using structuring element *SE*

$$TH_O = OI - (OI \circ SE) \tag{5.1}$$

Where $\circ$ is morphological opening operation.

Similarly the dual top-hat by closing, TH_C, is the difference between the grayscale closing using the structuring element *SE* and the original image, *OI*:

$$TH_C = (OI \bullet SE) - OI \tag{5.2}$$

Where $\bullet$ is morphological closing operation.

Here the *SE* is "*ball*" shaped with height = 50 and radius = 17 respectively.

The top-hat by opening, yields an image that contains all the residual features (i.e. peaks and ridges) removed by the opening. Adding these residual features to the original image has the effect of accentuating high-intensity (light) structures.

The dual residual (i.e., valleys and troughs) obtained by using the top-hat by closing, is then subtracted from the resulting image to accentuate low-intensity (dark) structures:

$$IE = OI + TH_O - TH_C \tag{5.3}$$

Where, *IE* is the enhanced image. Block diagram of top-hat filtering based enhancement method is presented in *Fig-5.12*.

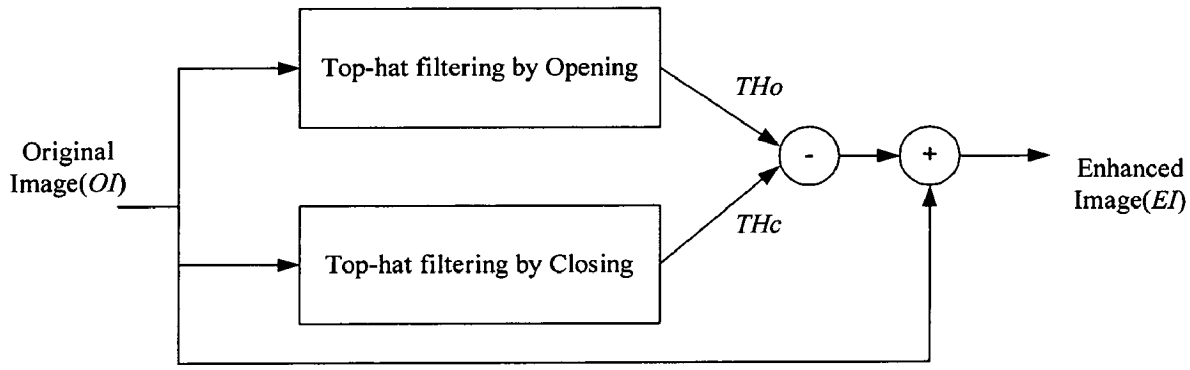


Fig-5.12- Block diagram of top-hat filtering based enhancement method

The result of applying morphological enhancement on mammogram image is depicted below in *Fig-5.13*.

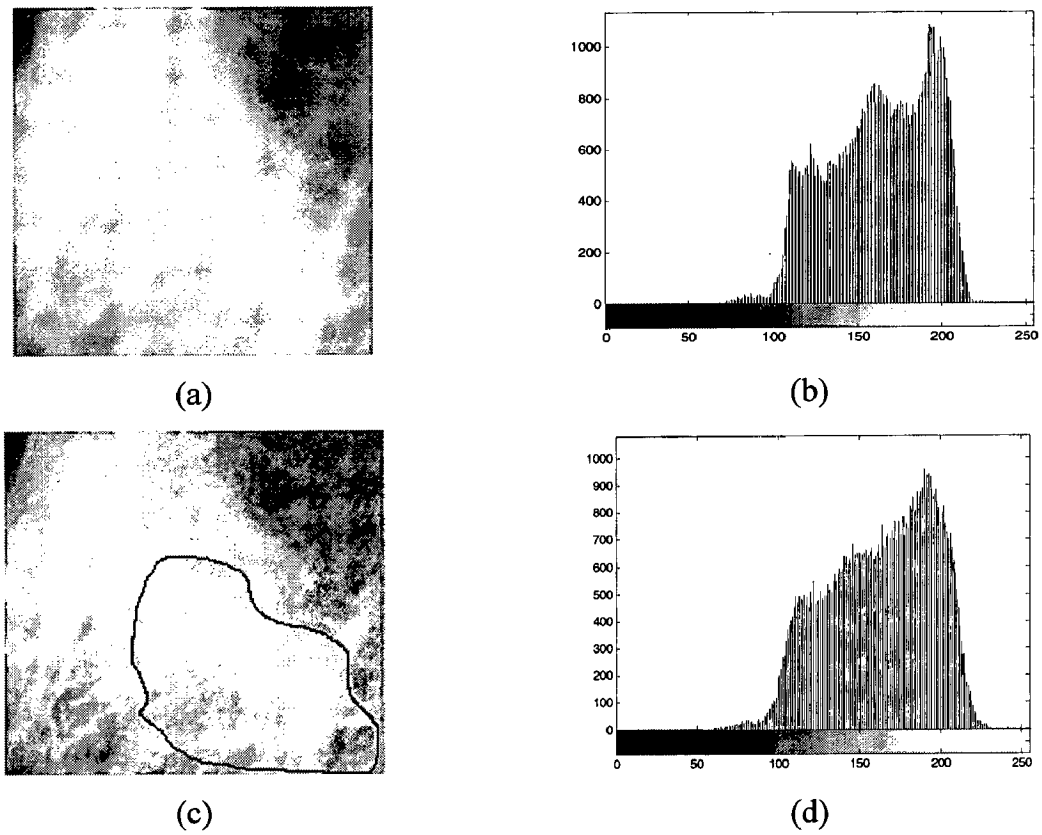


Fig-5.13- ROI Image from MIAS [2] (mdb209): (a) Original ROI Image (b) Original ROI Image Histogram (c) Enhanced ROI image and (d) Enhanced ROI Image Histogram.

It can be seen that ME, UM and CLAHE methods compresses the highest frequencies to lie around the mean whereas CS method stretches the histogram. But the ME gave better histogram compression as compared to other methods.

5.2.8 Unsharp masking and Contrast Stretch

To improve the visibility of mammographic features, the combination of two enhancement methods is proposed [3]. The result of enhancement by unsharp masking followed by contrast stretching is shown in *fig. 5.14* below.

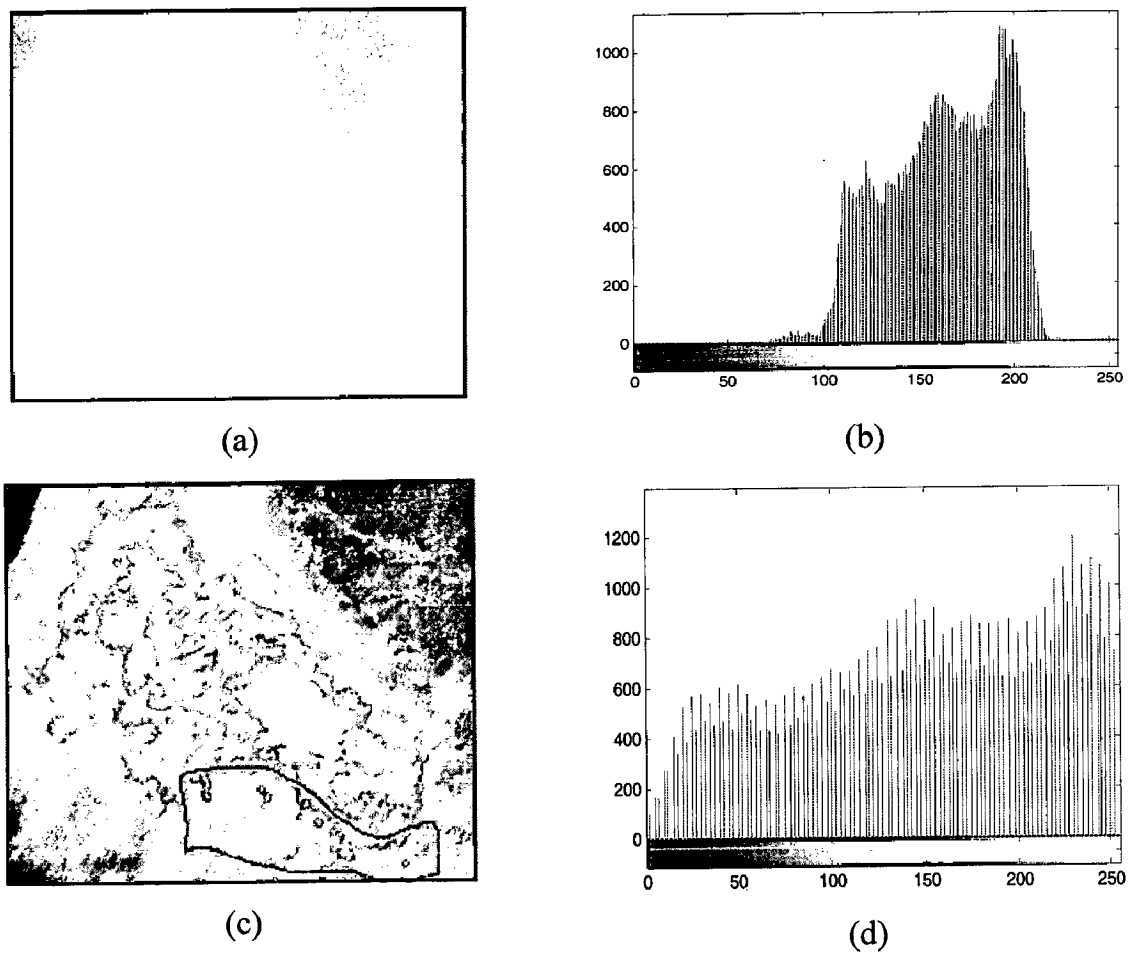


Fig-5.14- ROI image from MIAS [2] (mdb209): (a) Original ROI image (b) Original ROI image histogram (c) Enhanced ROI image and (d) Enhanced ROI image histogram.

5.2.9 Morphological Enhancement and Contrast Stretch

The results of enhancement by morphological enhancement followed by contrast stretching is shown in *Fig-5.15* below.

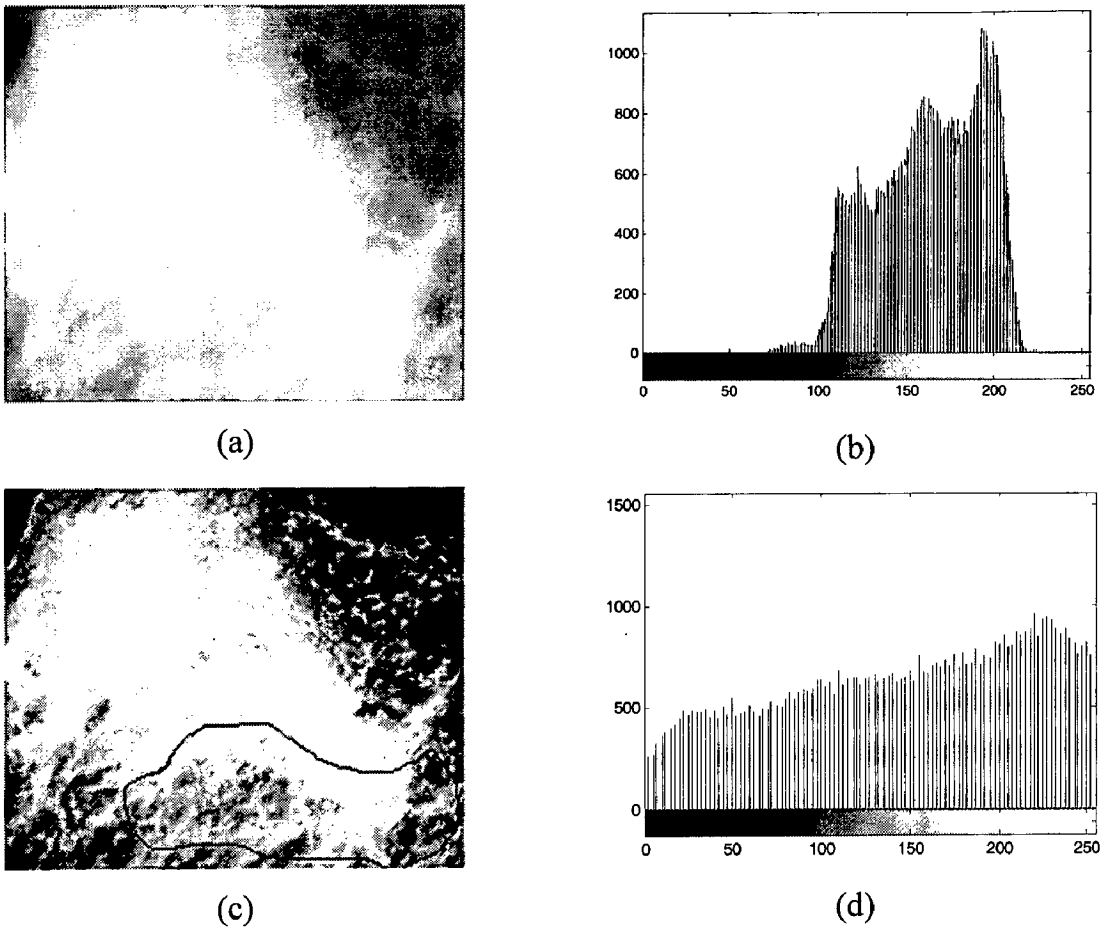


Fig-5.15- ROI image from MIAS [2] (mdb209): (a) Original ROI image (b) Original ROI image histogram (c) Enhanced ROI image and (d) Enhanced ROI image histogram.

5.2.11 Visual Comparison between original ROI , unsharp masking and contrast stretch and morphological enhancement and contrast stretch.

The resulting images are shown below in Fig-5.16 below-

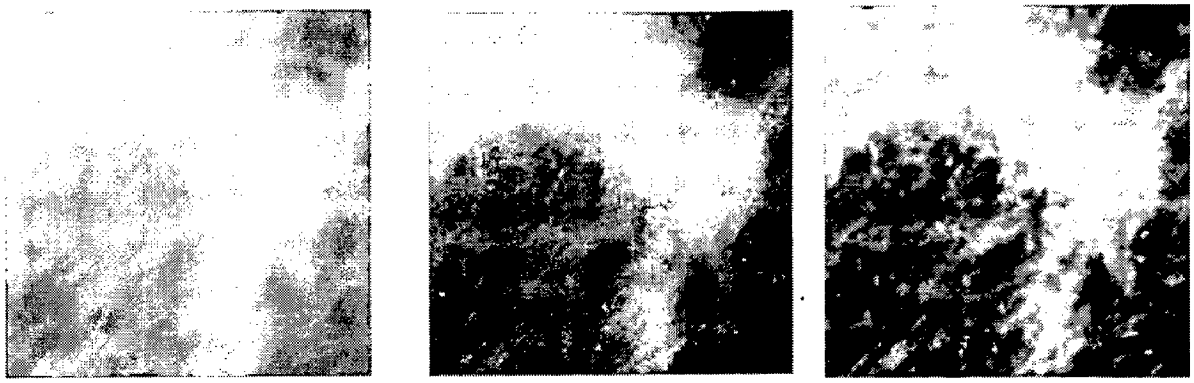


Fig-5.16- ROI image from MIAS [2] (mdb209): (a) Original ROI image (b) Original ROI image histogram (c) Enhanced ROI image (UM+CS) and (c) Enhanced ROI image (ME+CS).

It can be observed that the combination unsharp masking and contrast stretching gives better results as compared to morphological enhancement and contrast stretching.

However, contrast stretching involves modifying the histogram i.e. it is an indirect method so morphological enhancement is the best direct method for enhancing mammograms.

Chapter 6

EVALUATION OF CONTRAST ENHANCEMENT TECHNIQUES

Introduction- Digital mammography is believed to help breast image experts to detect breast cancer early. Early detection and diagnosis of breast cancer markedly increases survival rate. Accurate diagnosis also depends on the quality of the image presented to experts. This study addresses the various quantitative methods for evaluation of quality improvement of the image.

CII (contrast improvement index) , (PSNR) peak signal to noise ratio, (ASNR) average signal to noise ratio, DSM (distribution separation measure) , (TBCs) Target-to-background contrast enhancement measurement based on standard deviation and (TBCe) Target –to-background contrast enhancement based on entropy have been used to evaluate the enhancement performance.

In this chapter a method to combine DSM, TBCs and TBCe into one quantitative value (D-Index) is proposed. Results in this study demonstrate that the proposed measures can be used to quantitatively rank enhancement techniques for a particular image.

6.1 Image Data

In this study, digital mammograms obtained from MIAS Mini-mammographic database [2] were used to calculate the quantitative measures for evaluation of contrast enhancement algorithms. The digital mammograms (digitized at 50 micron pixel edge) has been reduced to 200 micron pixel edge and clipped/padded so that every image is 1024 pixels x 1024 pixels. The ROI have been extracted according to data given in the database and the enhancement techniques are applied to extracted ROI's.

6.2 Image Contrast

In Practice, many definitions of contrast are used [24]. In general terms, contrast refers to the difference in luminance between an object and its surroundings. In psycho visual studies, the contrast C of an object with luminance f against its surrounding of luminance b is defined as follows:

$$C = \frac{f - b}{b}, \tag{6.1}$$

Where, f is the maximum luminance in the image and b is the minimum luminance.

6.3 Evaluation of Enhancement Techniques

The improvement in images after enhancement is often very difficult to measure. A processed image can be said to be an enhancement over the original image if it allows the observer to better perceive the desirable information in the image. In mammograms, the improved perception is difficult to quantify. Use of statistical measures of gray level distribution as measures of local contrast enhancement (for example, variance or entropy) have not been particularly meaningful for mammogram images. A number of images which clearly showed improved contrast showed no consistency, as a class, using these statistical methods.

Morrow et al. [20] propose a measure of contrast histogram that is the graph of distribution of contrast over image. The width of the contrast histogram can be quantified by the second moment,

$$M_2 = \sum_{i=1}^{N} c_i^2 p(c_i), \tag{6.2}$$

Where c_i computed by using the Eq. (6.4) are the contrast values falling in the ith bin of N bins, $p(c_i)$ is the normalized number of the occurrences of the contrast c_i. A low-contrast image has a narrow contrast histogram, while a high-contrast image has a broader contrast histogram. The second moment M_2 for the enhanced image is bigger than that of the original image, and it indicates that the contrast spread is wider in the enhanced image.

Laine et al. [8] proposed the contrast improvement index CII as the measure of the enhancement performance:

$$CII = C_{processed} / C_{original}, \tag{6.3}$$

Where $C_{processed}$ and $C_{original}$ are the contrasts for a ROI in the processed and the original images, respectively. The contrast C of a region is defined by

$$C = \frac{f-b}{f+b}, \tag{6.4}$$

Where f is the mean gray-level value of the foreground and b is the mean gray-level value of the background. The bigger the value of CII, the better the performance.

Li et al . [22,23] used contrast, contrast improvement index (CII), background noise level, peak signal to noise ratio (PSNR) , and average signal to noise ratio (ASNR) to evaluate the enhancement performance. The definition of CII is the same as given by Eqs. (6.3) and (6.4) [8], and the background noise level is measured by the standard deviation σ of the background :

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(b_i - b)^2}, \tag{6.5}$$

where b_i is the gray-level value of a surrounding background region.

$$PSNR = \frac{p-b}{\sigma} \tag{6.6}$$

$$ASNR = \frac{f-b}{\sigma}, \tag{6.7}$$

Where p is the maximum gray-level value of the foreground. The larger the values of the ASNR and PSNR, the better is the enhancement performance.

6.4 Distribution Separation Measure (DSM)

For evaluating DSM the Target T and background B are first defined. Original image A is enhanced as B. Analysis images are C and D as shown in *Fig-6.1* below.

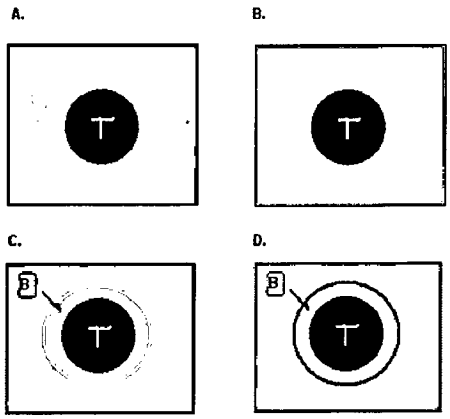


Fig-6.1- (a) Original image (b) Enhanced image (c) & (d) Original and enhanced analysis images with target and background marked.

$$DSM = (|\mu^{E}_{T} - \mu^{E}_{B}|) - (|\mu^{O}_{T} - \mu^{O}_{B}|) \qquad (6.8)$$

Here, μ^{O}_{B} ,σ^{O}_{B} , μ^{O}_{T} ,σ^{O}_{T} are the mean and standard deviation of the gray-scales comprising the background and target area, of the original image before enhancement.

Similarly, μ^{E}_{B} ,σ^{E}_{B} , μ^{E}_{T} ,σ^{E}_{T} correspond to the mean and standard deviation of the gray scale after the enhancement. The greater the DSM value the better is the quality of enhancement.

6.5 TBCs

The objective of contrast enhancement is to maximize the difference between background and target mean gray level. Using the ratio of the standard deviation of the gray-scales within the target before and after enhancement, we can quantify this improvement using TBCs as below-

$$TBCs = \{ ((\mu^{E}_{T}/ \mu^{E}_{B}) - (\mu^{O}_{T}/ \mu^{O}_{B}))/ (\sigma^{E}_{T}/ \sigma^{O}_{T})\} \qquad (6.9)$$

It is expected as a result of enhancement, this measure should give the value greater than zero.

6.6 TBCe

The concept of TBCs can be extended by replacing the standard deviation with entropy of the target in the original and enhanced images, ε^{O}_{T} and ε^{E}_{T}, respectively.

$$TBCe = \{ ((\mu^{E}_{T}/ \mu^{E}_{B}) - (\mu^{O}_{T}/ \mu^{O}_{B}))/ (\varepsilon^{E}_{T}/ \varepsilon^{O}_{T})\} \qquad (6.10)$$

It is expected as a result of enhancement, this measure should give the value greater than zero.

6.7 Combined Enhancement Measure D

The above methods DSM, TBCs and TBCe can be combined to give one quantitative value [29]. To combine DSM, TBCs and TBCe for a particular enhancement, we represent each enhancement value with in a three-dimensional (3-D)Euclidean space.

$$D=\{(1-DSM)^2 + (1-TBCs)^2 + (1-TBCe)^2\}^{1/2} \qquad (6.11)$$

The enhancement method giving the smallest value of D is selected as the best enhancement method for the image.

6.8 D Index Comparison- Performance Evaluation

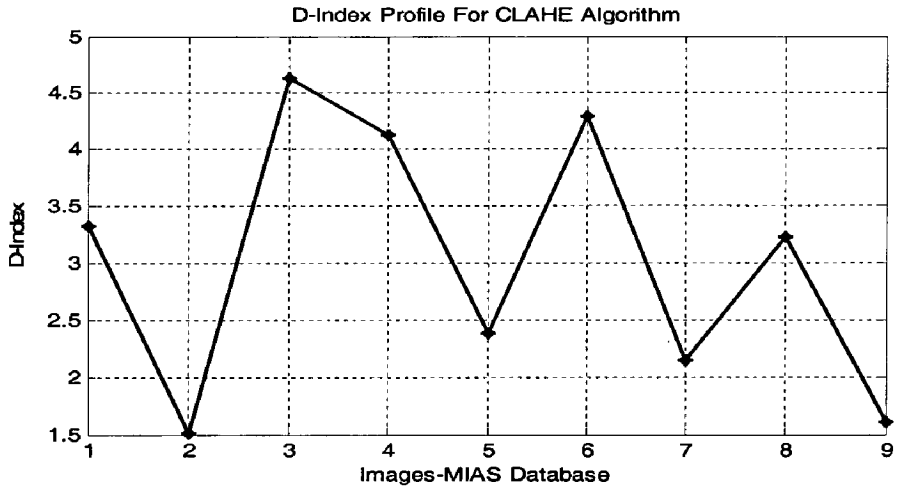
The performance of the morphological enhancement (ME) scheme and Wavelet based sub-band filtering technique (WL) is compared with conventional Contrast-Limited Adaptive Histogram Equalization (CLAHE) algorithm, Contrast Stretching (CS) and Unsharp Masking (UM).

It is characterized through a process of direct visual inspection, quantitative measures and comparative measures such as image profiles.

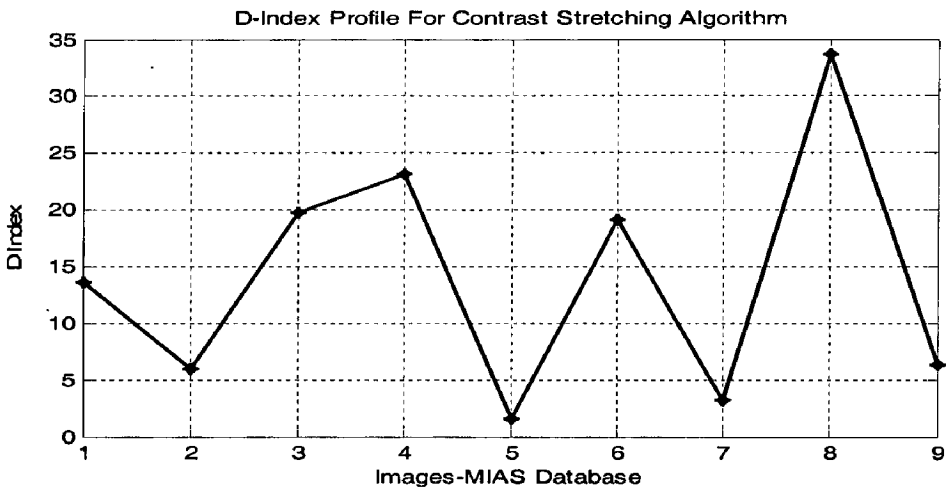
The quantitative measures used here are, the D index used as contrast enhancement measure (CEM) given by S. Singh et al. [29], detail variance (DV), background variance (BV) and DV/BV ratio [30] . Reasonably high values of DV in the enhanced images are expected, while the BV value should remain low in order to indicate limited noise amplification.

Table-6.1- Comparison of contrast enhancement D index for different enhancement techniques applied on ROI's of mammograms containing Microcalcifications- Data Source-MIAS database (biopsy proven malignant cases).

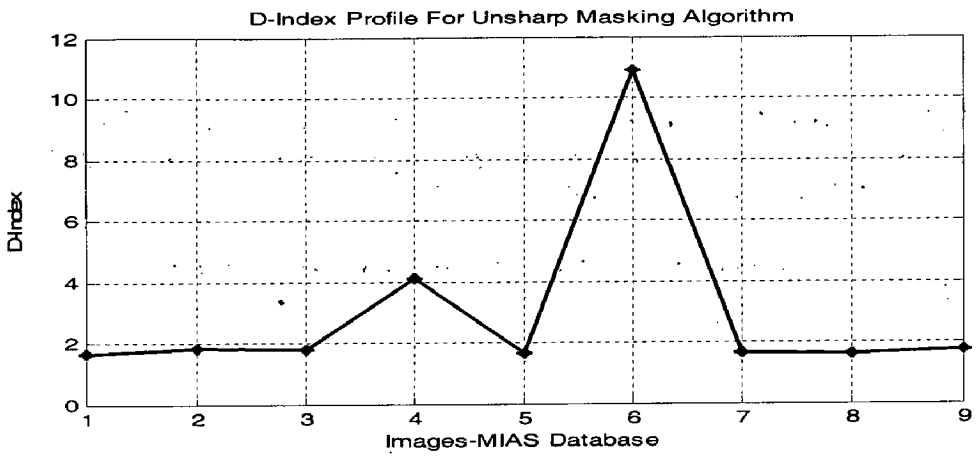
	D Index [29]				
File Name	CLAHE	CS	UM	WL	ME
mdb209	3.3192	13.5741	1.6472	1.7037	1.4275
mdb213	1.5062	5.9092	1.8253	1.7142	1.8037
mdb231	4.6298	19.7313	1.8039	4.3348	1.4094
mdb238	4.1257	23.1292	4.1257	4.0988	1.4861
mdb239	2.3823	1.5118	1.6398	1.6123	1.5736
mdb241	4.2869	19.1926	10.9084	3.6349	5.8997
mdb249	2.1457	3.2342	1.6678	1.5093	1.5084
mdb253	3.2225	33.6477	1.6197	1.2879	1.6484
mdb256	1.6010	6.3877	1.7323	2.0865	1.68753



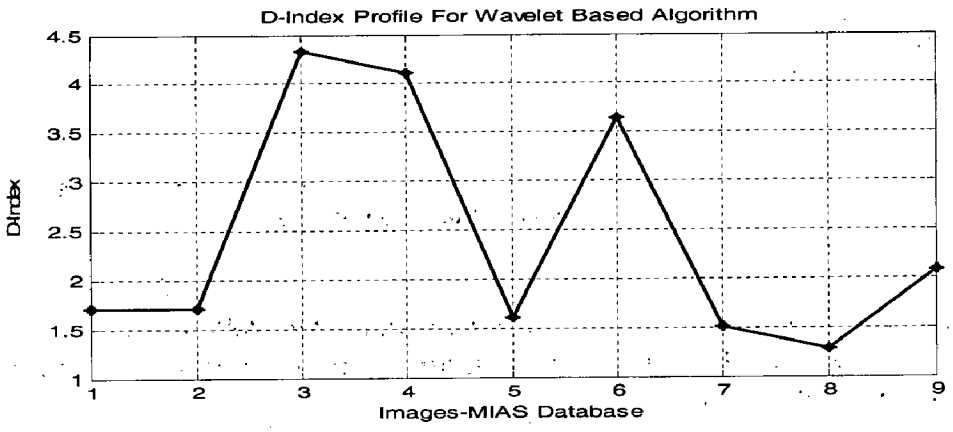
(a)



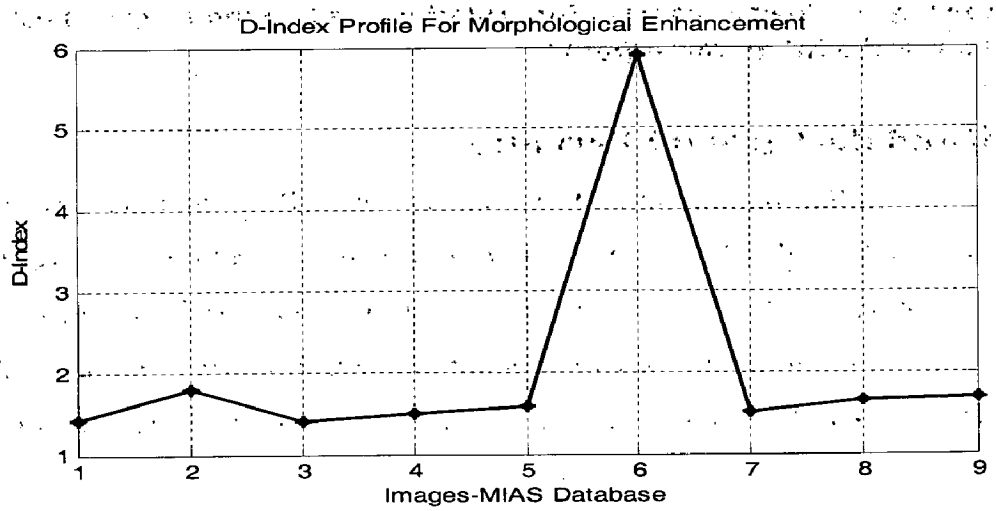
(b)


D-Index Profile For Unsharp Masking Algorithm
DIndex
Images-MIAS Database

(c)


D-Index Profile For Wavelet Based Algorithm
DIndex
Images-MIAS Database

(d)


D-Index Profile For Morphological Enhancement
DIndex
Images-MIAS Database

(e)

Fig-6.2- D-Index profile for different enhancement methods as applied to some ROIs of digital mammograms containing microcalcifications obtained from MIAS database[2]- a)CLAHE b)CS c) UM d)WL and e)ME.

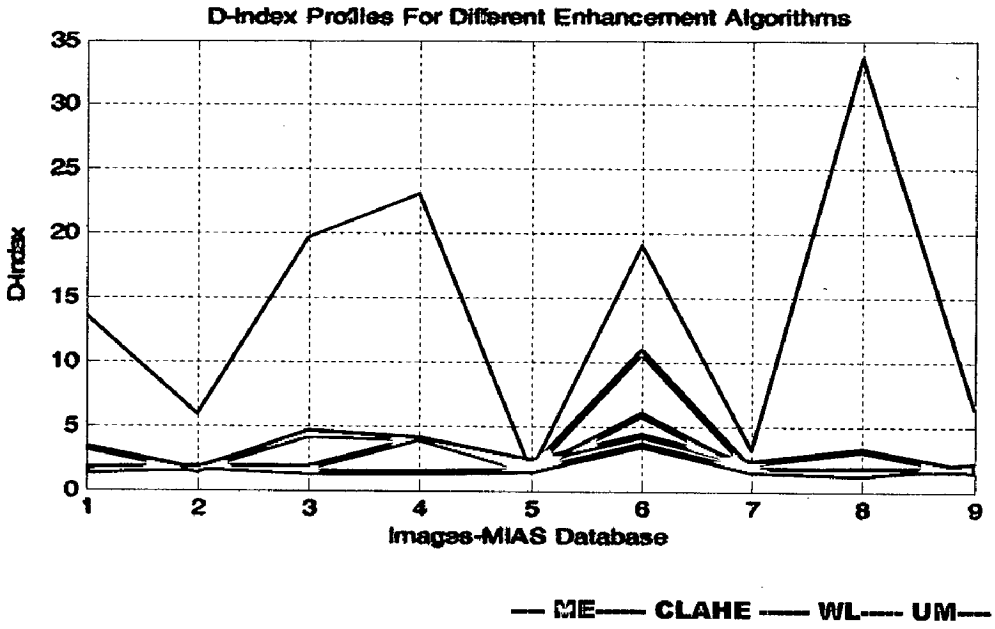


Fig-6.3- Comparison of contrast evaluation D-Index for different enhancement methods as applied to some ROI's of digital mammograms containing microcalcifications obtained from MIAS database.

By looking at Fig-6.3 it is verified that both WL and ME methods of enhancement give lower values for D-Index and hence are best suited for enhancement of digital mammograms.

6.9 Detail and Background Variance

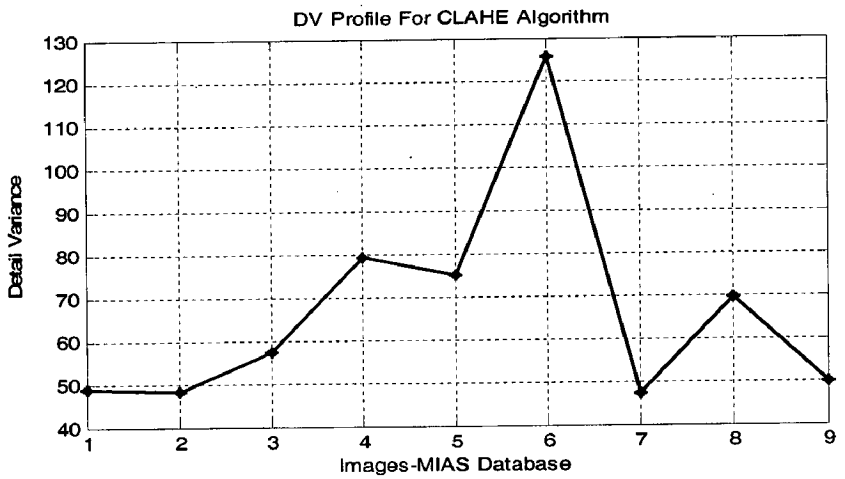
To further validate the results of ME enhancement method the comparisons of DV and BV are presented in *Tables-6.2 and 6.3* respectively. From *Table-6.2* it is found that there is highest increase in DV with ME method as compared to HISTEQ and CLAHE methods. Whereas the increase in BV with ME method is smallest while with HISTEQ and CLAHE methods increase in BV is more as evident from *Table-6.3.*

The comparisons for DV and BV are given in *Fig-6.3* and *Fig-6.4* respectively. From these results, it can be concluded that HISTEQ and CLAHE methods increase the background noise also along with the foreground microcalcifications.

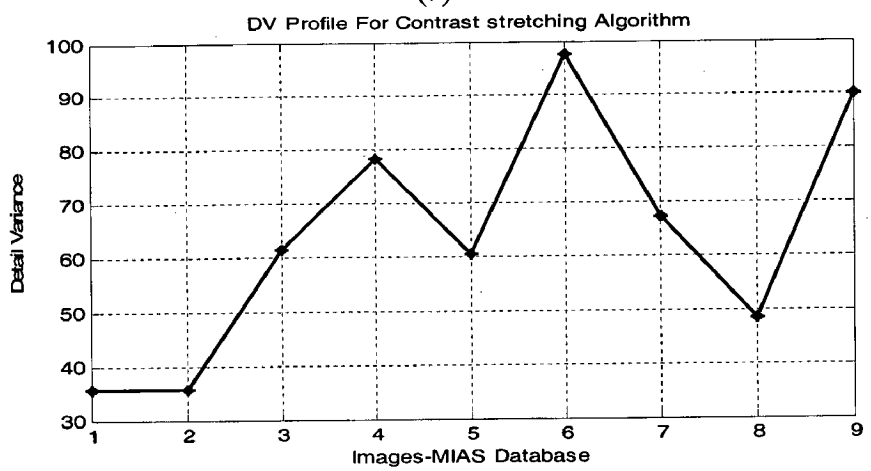
But the ME method enhances more of foreground information as compared to background.

Table-6.2- Comparison of detail variance (DV) for different enhancement techniques applied on ROI's of mammograms containing microcalcifications.

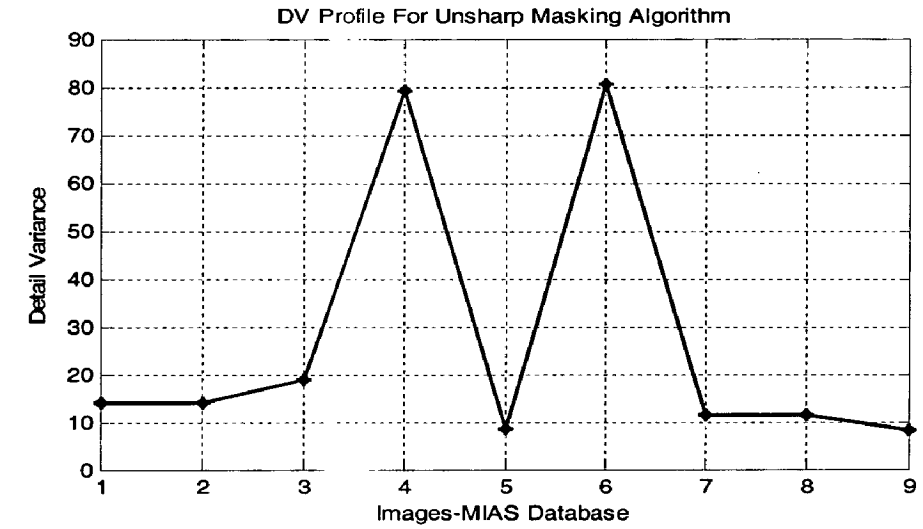
File Name	DV [29]				
	CLAHE	CS	UM	WL	ME
mdb209	48.9646	35.7127	13.9356	6.6934	36.5289
mdb213	48.2644	35.5263	14.1112	3.2423	36.9869
mdb231	57.3799	61.4642	18.7568	4.5695	47.8805
mdb238	79.0712	78.3276	79.0712	4.0805	38.7903
mdb239	74.9426	60.4257	8.4315	1.8743	22.4341
mdb241	125.5512	97.6296	80.5354	72.9921	97.3134
mdb249	47.3485	67.1603	11.3531	2.6139	29.6802
mdb253	69.5278	48.5542	11.5996	3.4329	29.5471
mdb256	49.7670	90.0246	8.3248	1.6430	20.3828



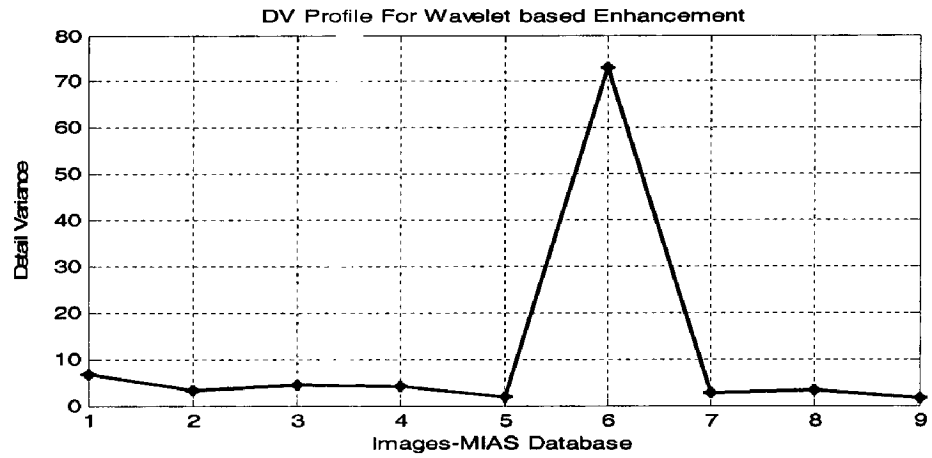
(a)



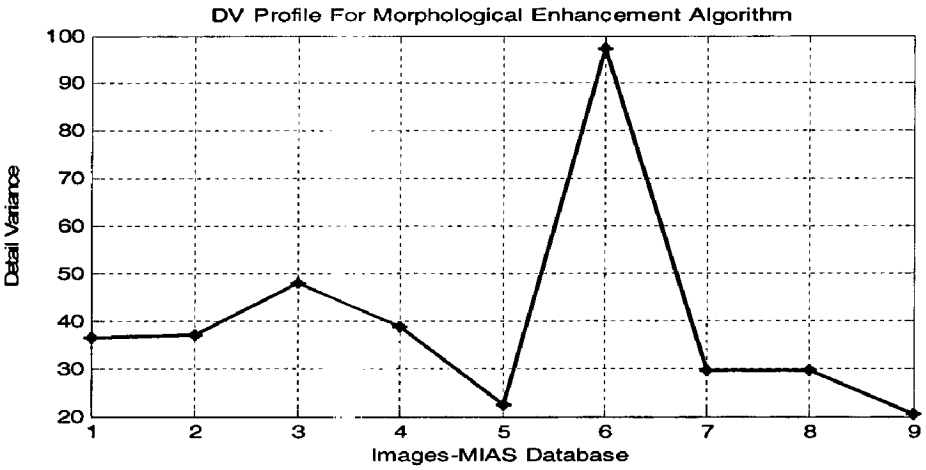
(b)



(c)



(d)



(e)

Fig-6.4- DV profile for different enhancement methods as applied to some ROI's of digital mammograms containing microcalcifications obtained from MIAS database- a)CLAHE b)CS c) UM d)WL and e)ME.

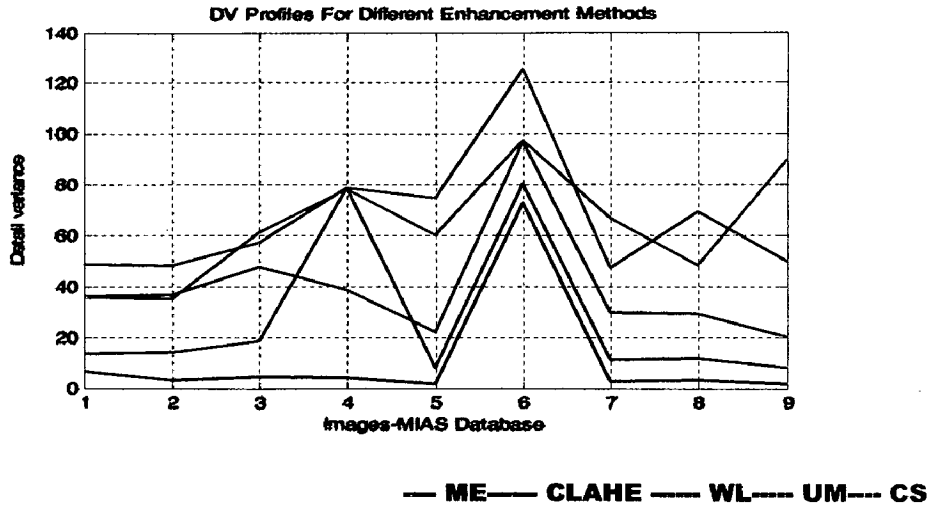
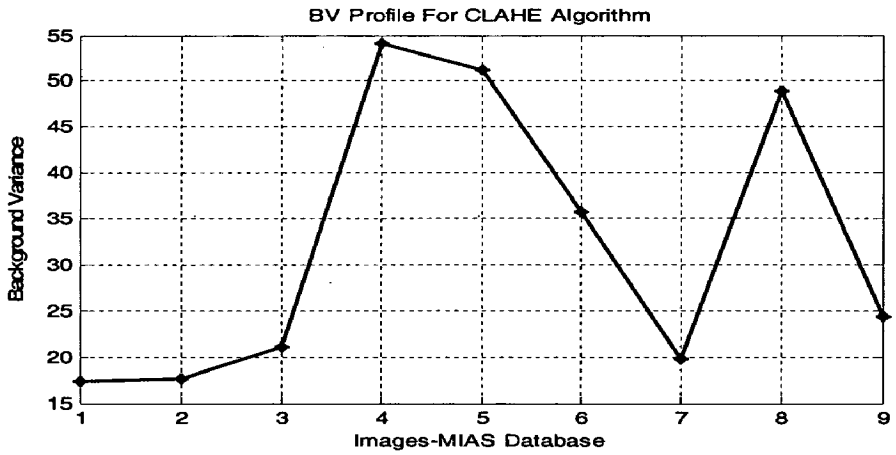


Fig-6.5- Comparison of detail variance (DV) for different enhancement methods as applied to some ROI's of digital mammograms containing microcalcifications obtained from MIAS database.

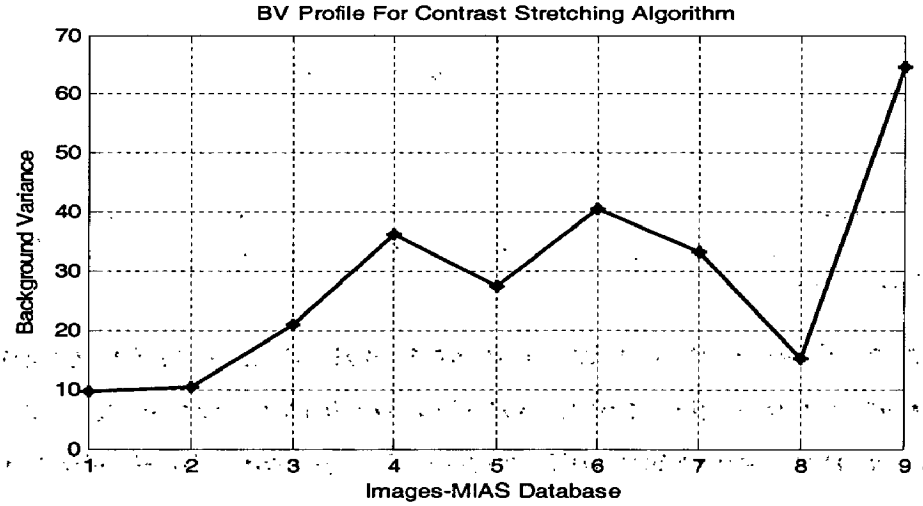
By looking at Fig-6.5, it can be observed that DV profile for CLAHE algorithm has maximum area under the curve, but this method is not suited because of the fact that noise is also enhanced with microcalcifications. Next, Profile obtained by CS method of enhancement has second maximum area under its profile, but it is not usually adopted as it is an indirect method of enhancement, therefore , ME method of enhancement ,which is a direct method is ideally suited for enhancement of mammograms containing MCC's.

Table-6.3- Comparison of background variance (BV) for different enhancement techniques applied on ROI's of mammograms containing microcalcifications.

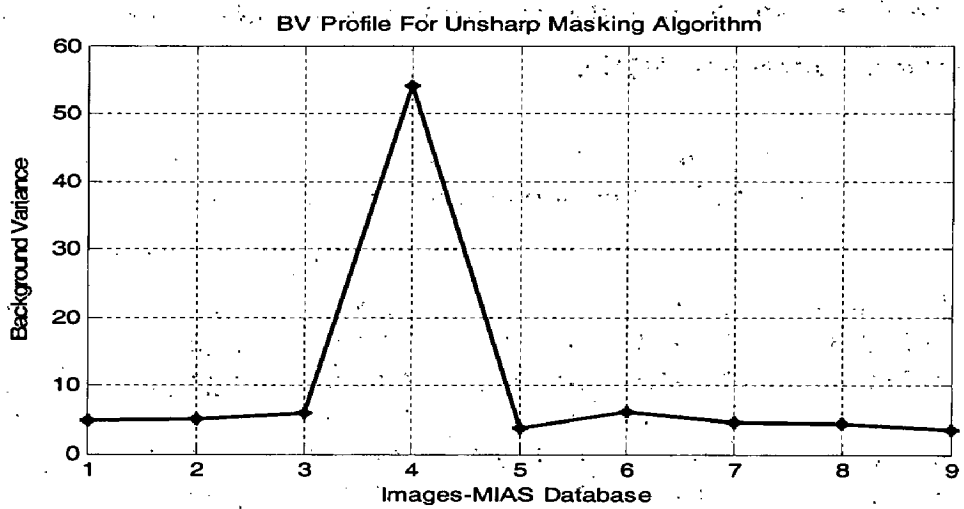
File Name	BV [29]				
	CLAHE	CS	UM	WL	ME
mdb209	17.3944	9.5652	4.7700	1.6413	12.0314
mdb213	17.6010	10.3249	5.1080	3.2528	12.6738
mdb231	21.1301	20.8569	5.8798	3.5126	15.0379
mdb238	54.0597	36.1667	54.0597	2.9217	13.4940
mdb239	51.1653	27.5353	3.7581	1.8715	8.8820
mdb241	35.7050	40.4044	6.0585	3.6602	14.7448
mdb249	19.7809	33.3265	4.6600	2.3585	11.2276
mdb253	48.8564	15.1669	4.3335	2.8014	10.3189
mdb256	24.3420	64.6516	3.5949	1.6249	8.0977


BV Profile For CLAHE Algorithm
Background Variance
Images-MIAS Database
55
50
45
40
35
30
25
20
15
1
2
3
4
5
6
7
8
9

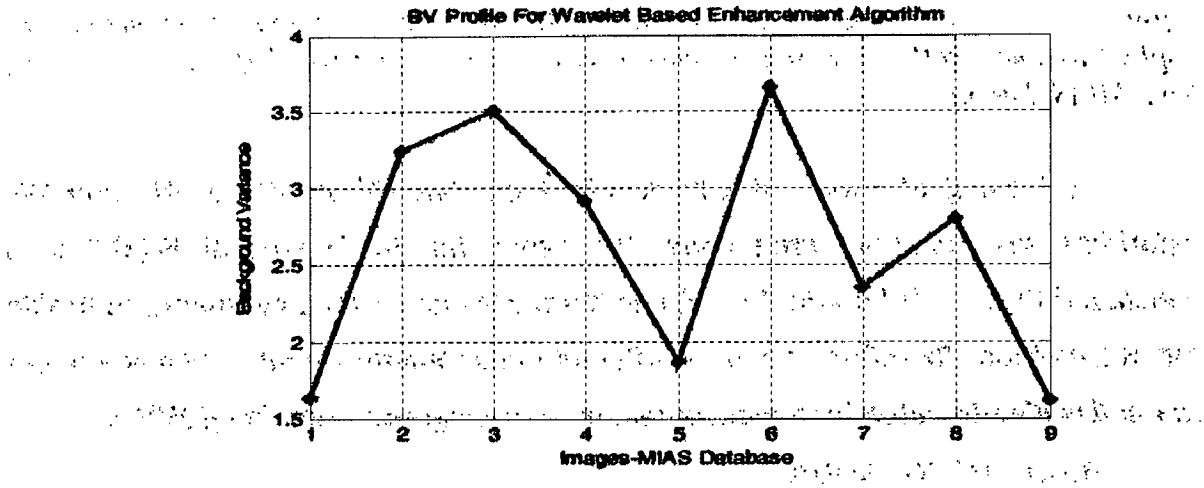
(a)


BV Profile For Contrast Stretching Algorithm
Background Variance
Images-MIAS Database
70
60
50
40
30
20
10
0
1
2
3
4
5
6
7
8
9

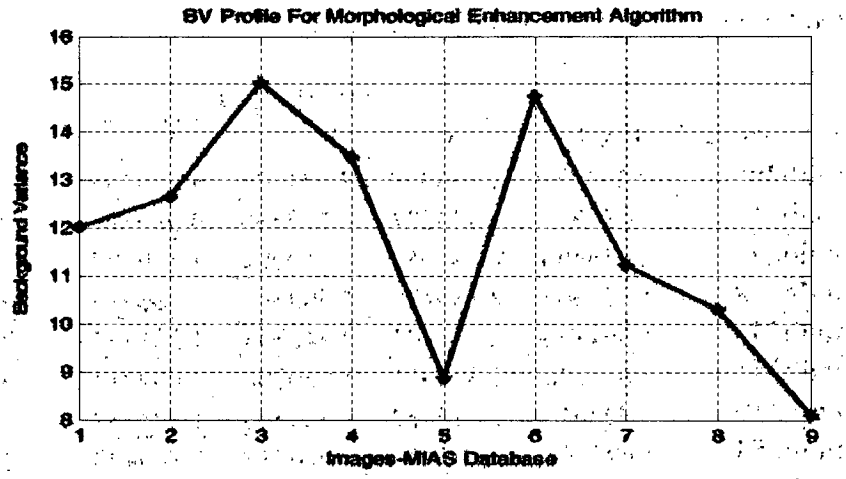
(b)


BV Profile For Unsharp Masking Algorithm
Background Variance
Images-MIAS Database
60
50
40
30
20
10
0
1
2
3
4
5
6
7
8
9

(c)



(d)



(c)

Fig-6.6- BV profile for different enhancement methods as applied to some ROIs of digital mammograms containing microcalcifications obtained from MIAS database-a)CLAHE b)CS c) UM d)WL and e)ME.

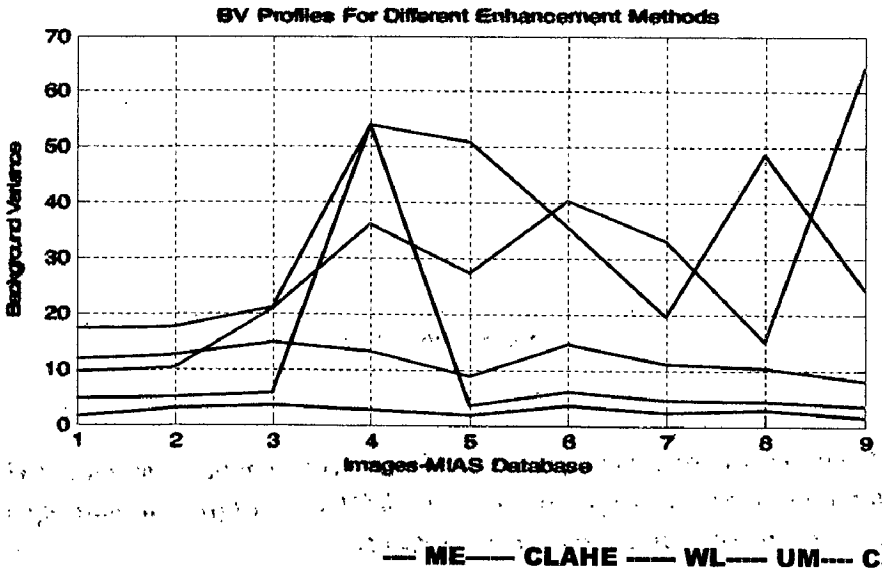


Fig-6.7- Comparison of background variance (BV) for different enhancement methods as applied to some ROI's of digital mammograms containing microcalcifications obtained from MIAS database.

By looking at Fig-6.7 it can be observed that BV profile for ME and WL algorithm has minimum area under the curve. But by looking at Fig-6.5 it is concluded that the DV profile for ME has more area under it as compared to profile for WL method. Therefore, it can be ME method of enhancement ,which is a direct method is ideally suited for enhancement of mammograms containing MCC's.

6.9.1 DV/BV Ratio

Table-6.4- Comparison of DV/BV Ratio for different enhancement techniques applied on ROI's of mammograms containing microcalcifications.

File Name	DV/BV [29]				
	CLAHE	CS	UM	WL	ME
mdb209	2.814883	3.733607	2.921509	4.078109	3.03613
mdb213	2.74214	3.440837	2.762569	0.996772	2.918375
mdb231	2.715553	2.946948	3.19004	1.300888	3.183988
mdb238	1.462664	2.165738	1.462664	1.398618	2.874633
mdb239	1.464715	2.194481	2.243554	1.001496	2.525794
mdb241	3.516348	2.416311	13.29296	19.94211	6.599845
mdb249	2.393647	2.015222	2.436288	1.108269	2.643504
mdb253	1.423105	3.201327	2.676728	1.225423	2.863396
mdb256	2.044491	1.392457	2.315725	1.011139	2.51711

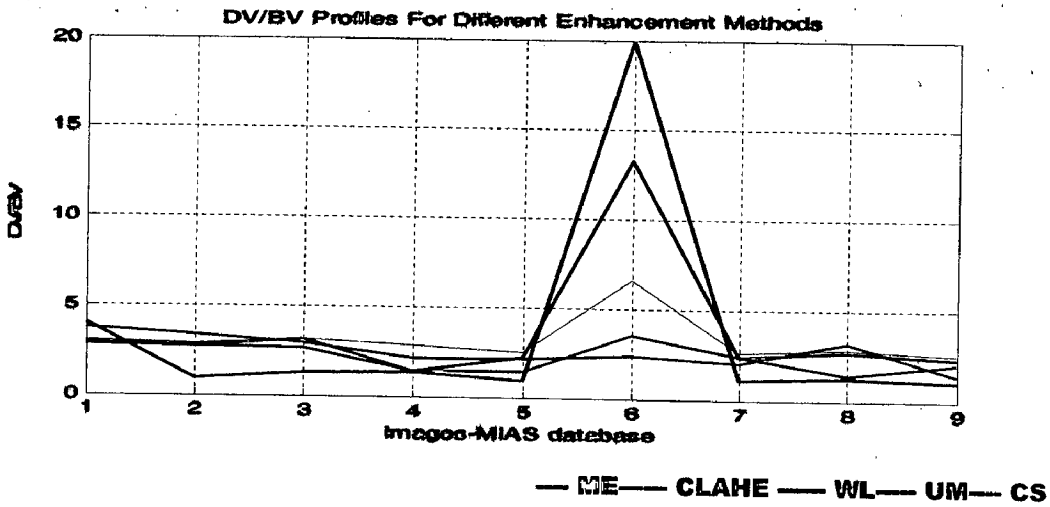


Fig-6.8- Comparison of detail variance (DV)/ background Variance (BV) for different enhancement methods as applied to some ROI's of digital mammograms containing microcalcifications obtained from MIAS database.

Reasonably high values of DV in the enhanced images indicate significant enhancement and lower values of BV indicate limited noise amplification.

The more the DV/BV ratio, the better is the enhancement algorithm. By looking at Fig-6.8 it can be observed that DV/BV profile for ME has maximum area under the curve. Therefore, it can be ME method of enhancement, which is a direct method is ideally suited for enhancement of mammograms containing Microcalcifications.

Observing the visual comparison, image profiles and image histograms of mammograms enhanced with the different methods further strengthens this conclusion.

6.10 Visual Comparison

Nine images enhanced by seven different enhancement algorithms were analyzed by the radiologist, with rich experience in mammography. According to the feedback from the radiologist, it was found that more number of calcifications are revealed for mammograms enhanced with morphological enhancement (ME) method , the same conclusion can be drawn by looking at the following illustrations.

Direct visual comparison of various enhancement methods are presented in *Fig-6.9* and *Fig-6.10*.

It can be seen that the MCCs have been enhanced better by the Morphological Enhancement (ME) method than by the other methods like contrast stretching (CS), contrast limited adaptive histogram equalization (CLAHE), unsharp masking (UM), and wavelet based sub-band filtering technique (WL).

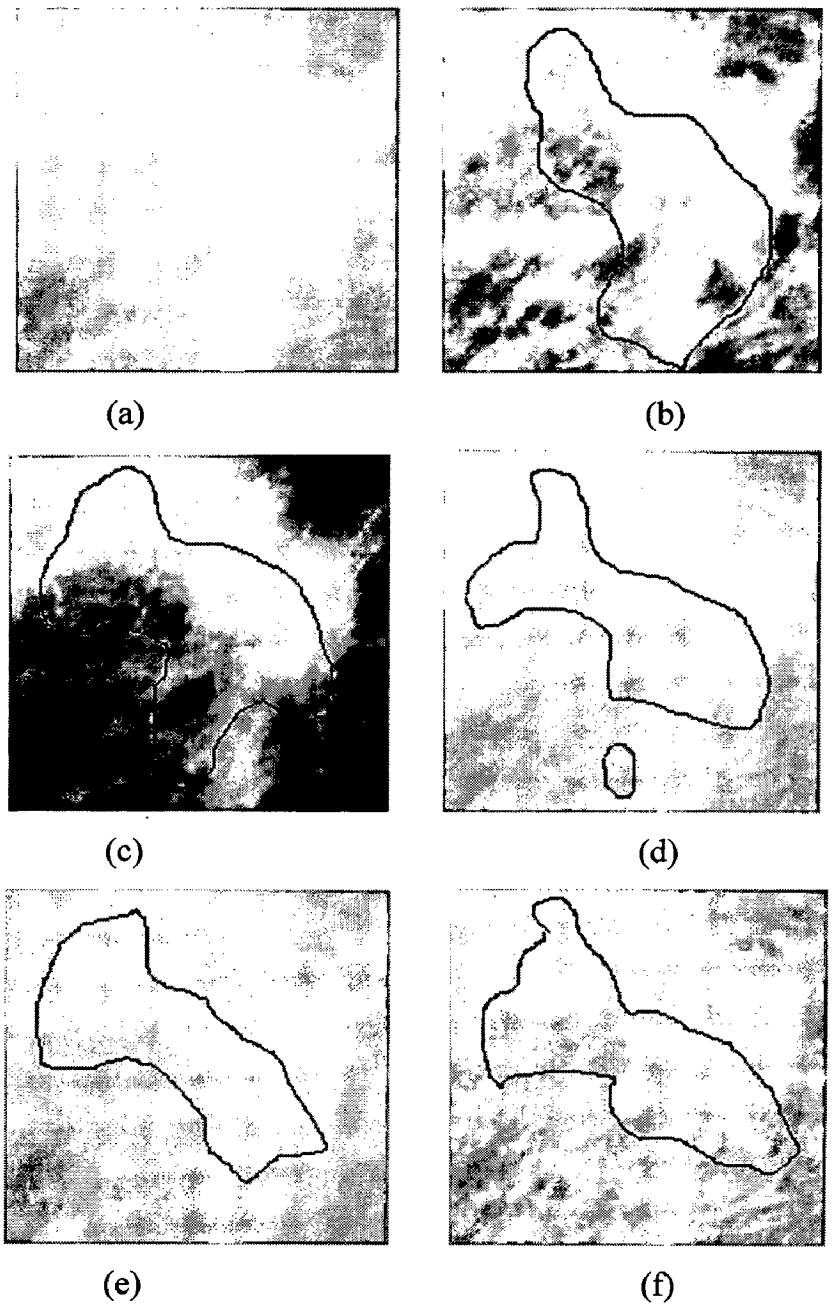


Fig-6.9- Comparative displays of different enhancement methods as applied to ROI's of digital mammograms containing microcalcifications (mdb209) (a) Original image, (b) image enhanced with CLAHE, (c) image enhanced with CS (d)image enhanced with UM (e)image enhanced with WL and (f) image enhanced with ME.

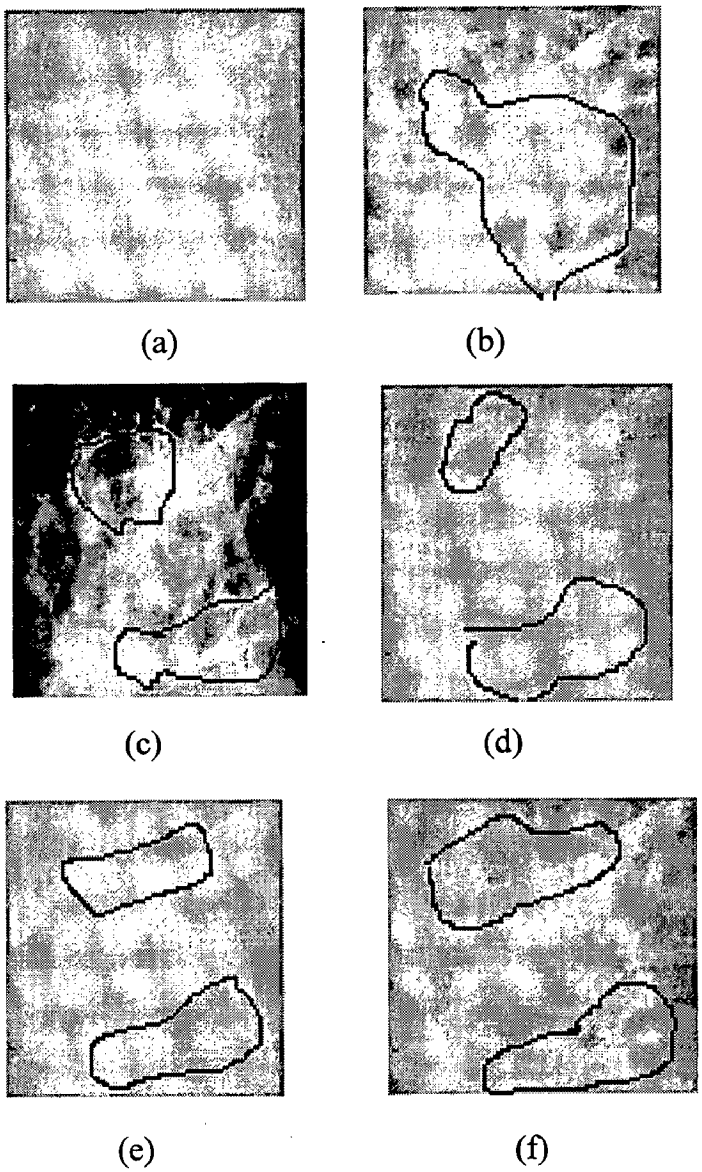


Fig-6.10- Comparative displays of different enhancement methods as applied to ROI's of digital mammograms containing microcalcifications (mdb213) (a) Original image, (b) image enhanced with CLAHE, (c) image enhanced with CS (d)image enhanced with UM (e)image enhanced with WL and (f) image enhanced with ME.

6.11 Image Profiles

The effect of enhancement can be visualized using a series of profiles taken across a series of microcalcifications from the ROI in *Fig-6.11*. The resulting profiles for the original, CS, CLAHE, UM,WL and ME are shown in *Fig-6.12*.

As clear from *Fig-6.13)*, it has been noticed that images enhanced with ME exhibit smooth transition in gray scales , thus indicating that it is not enhancing the background information as compared to other methods which contain spurious valleys pertaining to background noise. Therefore it can be concluded that ME method is only enhancing the microcalcifications but other methods enhance the background also, which is undesirable. Fig-6.11 below shows a ROI of the mammogram indicating the line along which image profile is taken.

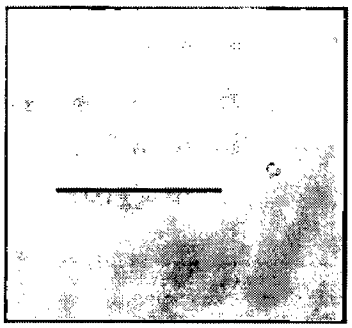
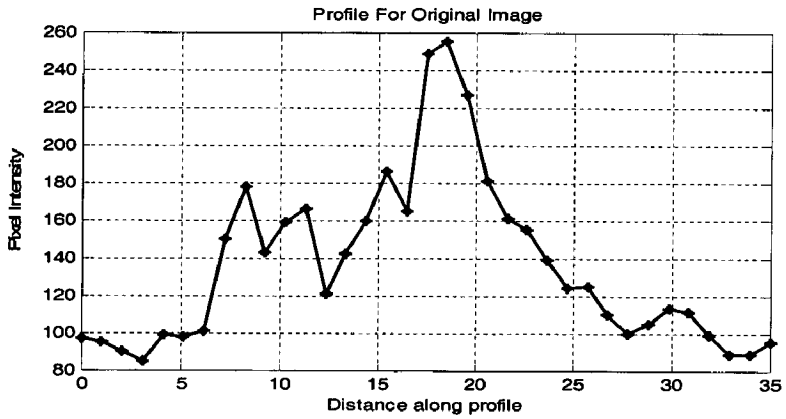
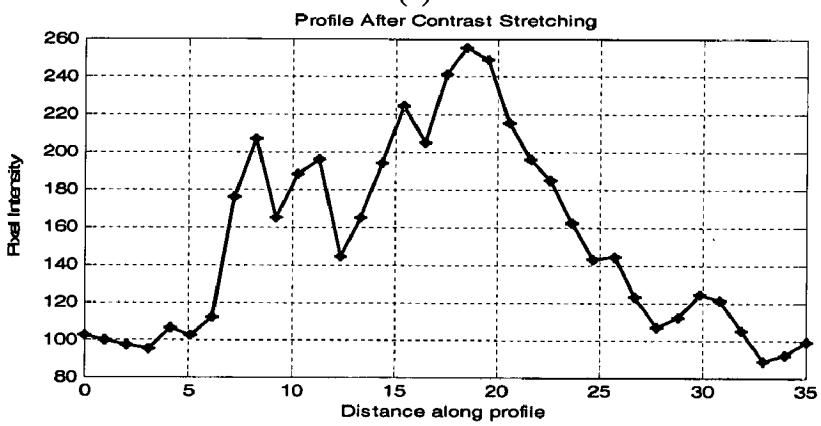


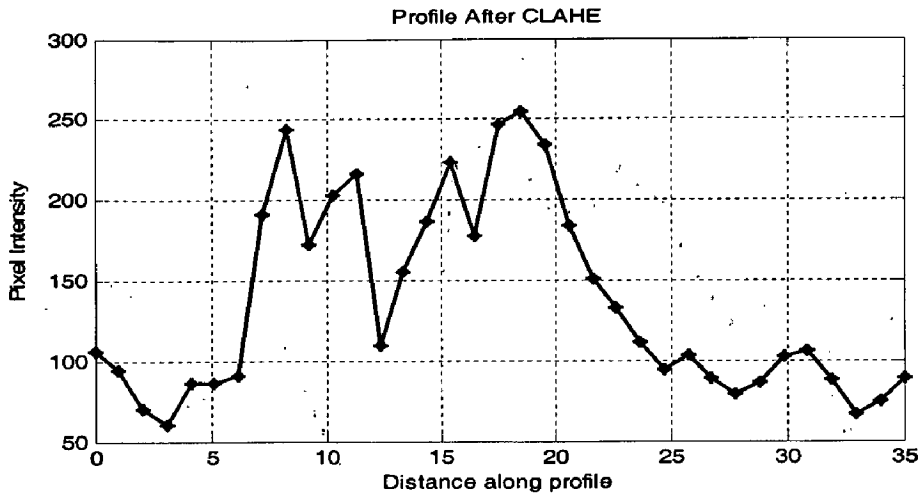
Fig-6.11- ROI of a mammogram, indicating the lines along which image profile is taken for microcalcifications



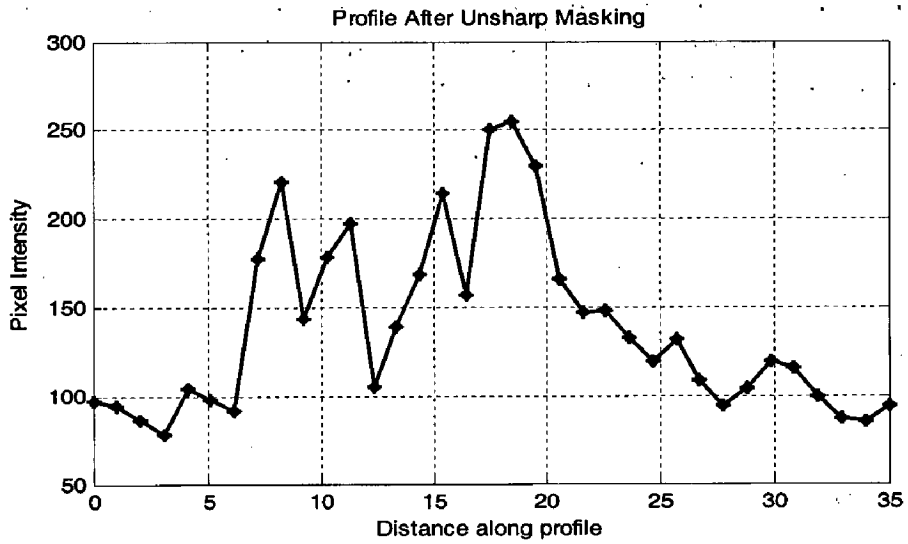
(a)



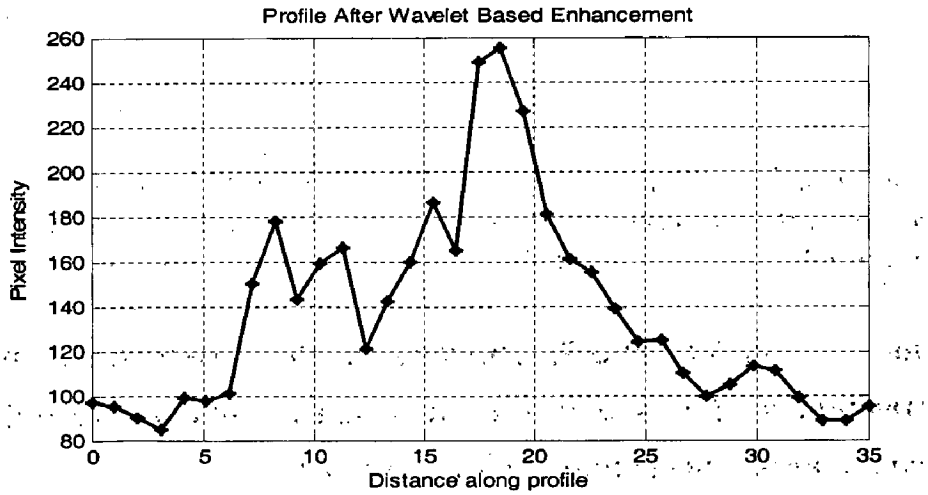
(b)


Profile After CLAHE
Pixel Intensity
Distance along profile
300
250
200
150
100
50
0
5
10
15
20
25
30
35

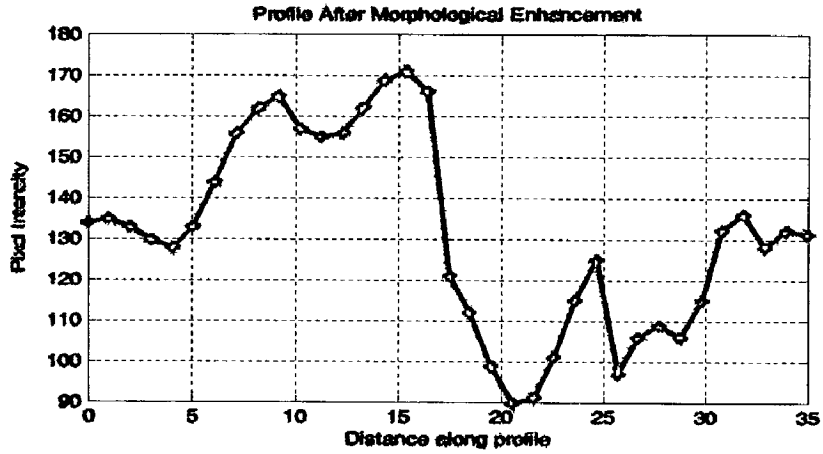
(c)


Profile After Unsharp Masking
Pixel Intensity
Distance along profile
300
250
200
150
100
50
0
5
10
15
20
25
30
35

(d)


Profile After Wavelet Based Enhancement
Pixel Intensity
Distance along profile
260
240
220
200
180
160
140
120
100
80
0
5
10
15
20
25
30
35

(e)



(f)

Fig-6.12- Image profile's for different enhancement methods as applied to some ROI's of digital mammograms containing microcalcifications obtained from MIAS database- (a)Original (b)CS (c)CLAHE d) UM (e)WL and (f)ME.

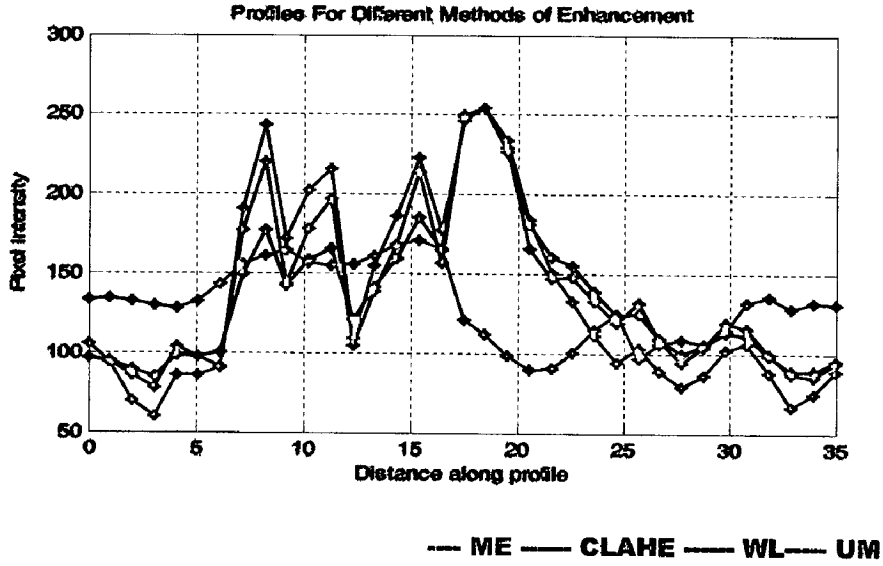
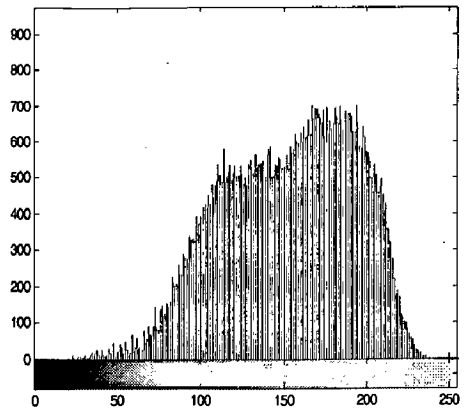


Fig-6.13- Image profiles (a) taken along line as in Fig-6.8(a) for microcalcifications in ROI enhanced with different enhancement methods, (b) taken along line as in Fig-6.8 (b) for background in ROI enhanced with different enhancement methods.

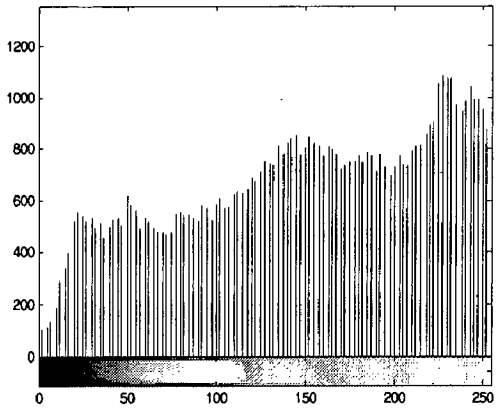
As shown in Fig-6.13 Profile obtained by ME enhancement method shows smoother transition in gray scales thus it indicates that profile obtained by ME method doesnot contain any spurious spikes (valleys).

6.12 Image Histograms

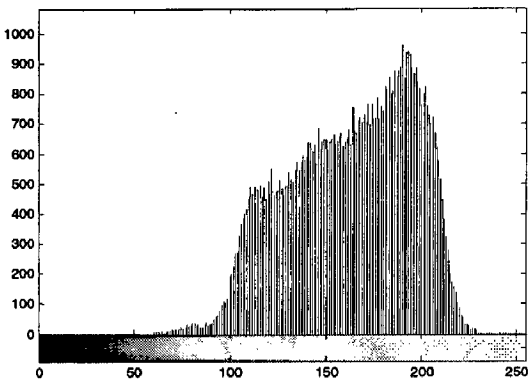
Histogram is a pictorial representation of gray scale intensity vs. gray scale frequency. The histograms of the enhanced images with five techniques are shown in *Fig-6.14* and *Fig- 6.15.*



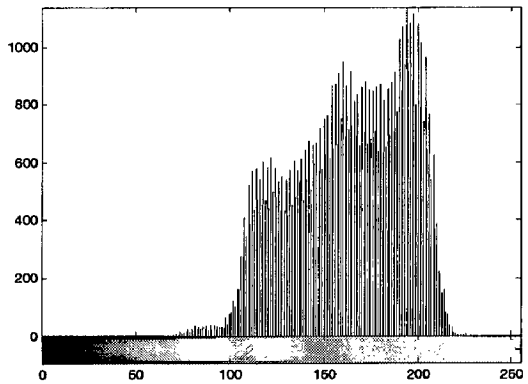
(a)



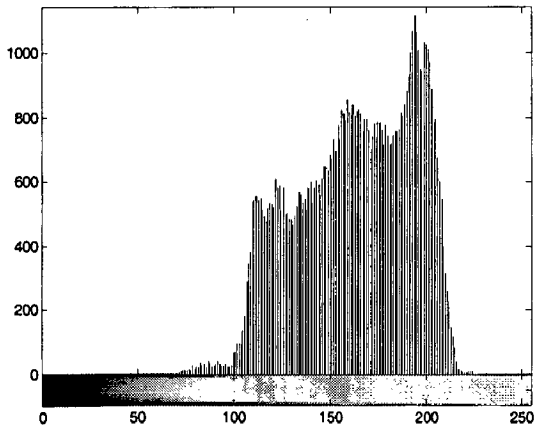
(b)



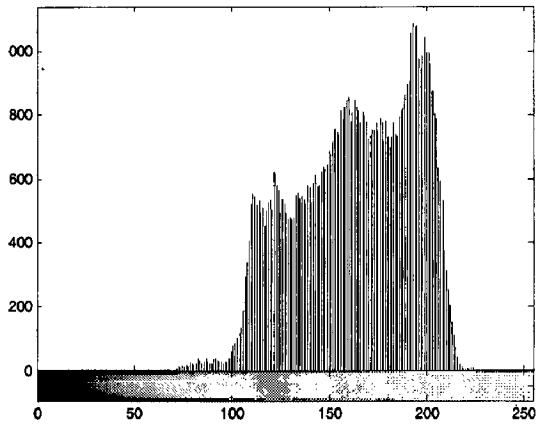
(c)



(d)



(e)



(f)

Fig-6.14- Gray level distributions (mdb209): (a) Original Image (b) image enhanced with CS (c) image enhanced with CLAHE (d)image enhanced with UM(e)image enhanced with WL(f) image enhanced with ME.

Chapter 7

Detection of Microcalcifications

Introduction- A microcalcification cluster is the type of breast cancer that is most difficult to detect with mammograms. They are small deposits of $Ca_5(PO_4)_3OH$ in breast tissue with size ranging from 0.05 to 1.0mm in diameter [9,10]. The clusters, which appear as bright specks on the photographic X-ray film [11,12], are very difficult to detect because they vary in size and shape [10], and they are embedded in and camouflaged by varying densities of parenchymal tissue structures[12].

It has been shown that early stages of breast cancer are indicated by the presence of one or more clusters of microcalcifications on the mammograms [13]. Mammogram screening increases the probability of detecting the existence of microcalcification clusters and applying the treatment appropriately. Hence, detection of microcalcification clusters with a high detection rate is crucial to the success of screening mammography.

Despite of its proven effectiveness, screening still misses about 20% of cancers. Several studies have shown that double reading of mammograms (by second radiologist) improves the accuracy of mammogram interpretation. The desire to use computers in place of second radiologist, or as a pre-screener to separate out clearly normal mammograms, is the motivations for computer aided detection research [16].

In this chapter both wavelet and morphological based techniques implemented for detecting the suspicious regions in a mammogram are explained.

7.1 Morphological Detection

Fig-7.1 shows a block diagram of procedure for detection of suspected microcalcifications.

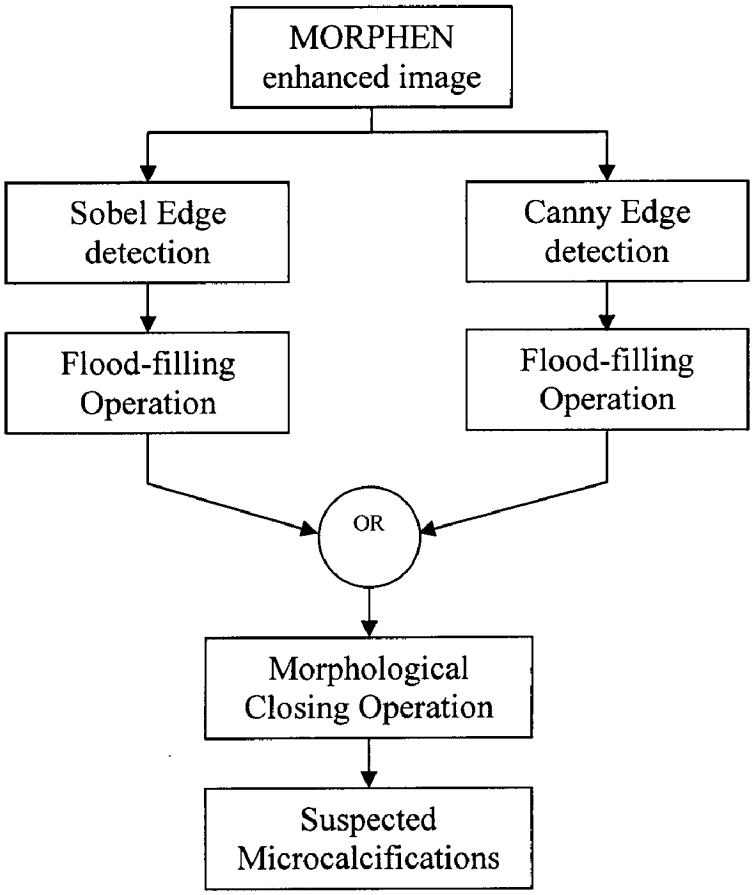


Fig-7.1- Block diagram for detection of suspected microcalcifications from enhanced mammogram ROI.

After enhancement of ROI with ME method, the enhanced image undergoes Sobel and Canny edge detection to segment the enhanced borders from the background image. The Sobel edge detector applies Sobel approximation to the derivative of the image and detects edges whenever the gradient of reconstructed input image is at its maximum [14].

The Canny edge detector finds edges by looking for local maximum of the gradient of unprocessed input image. In each edge detection algorithm, the gradient is

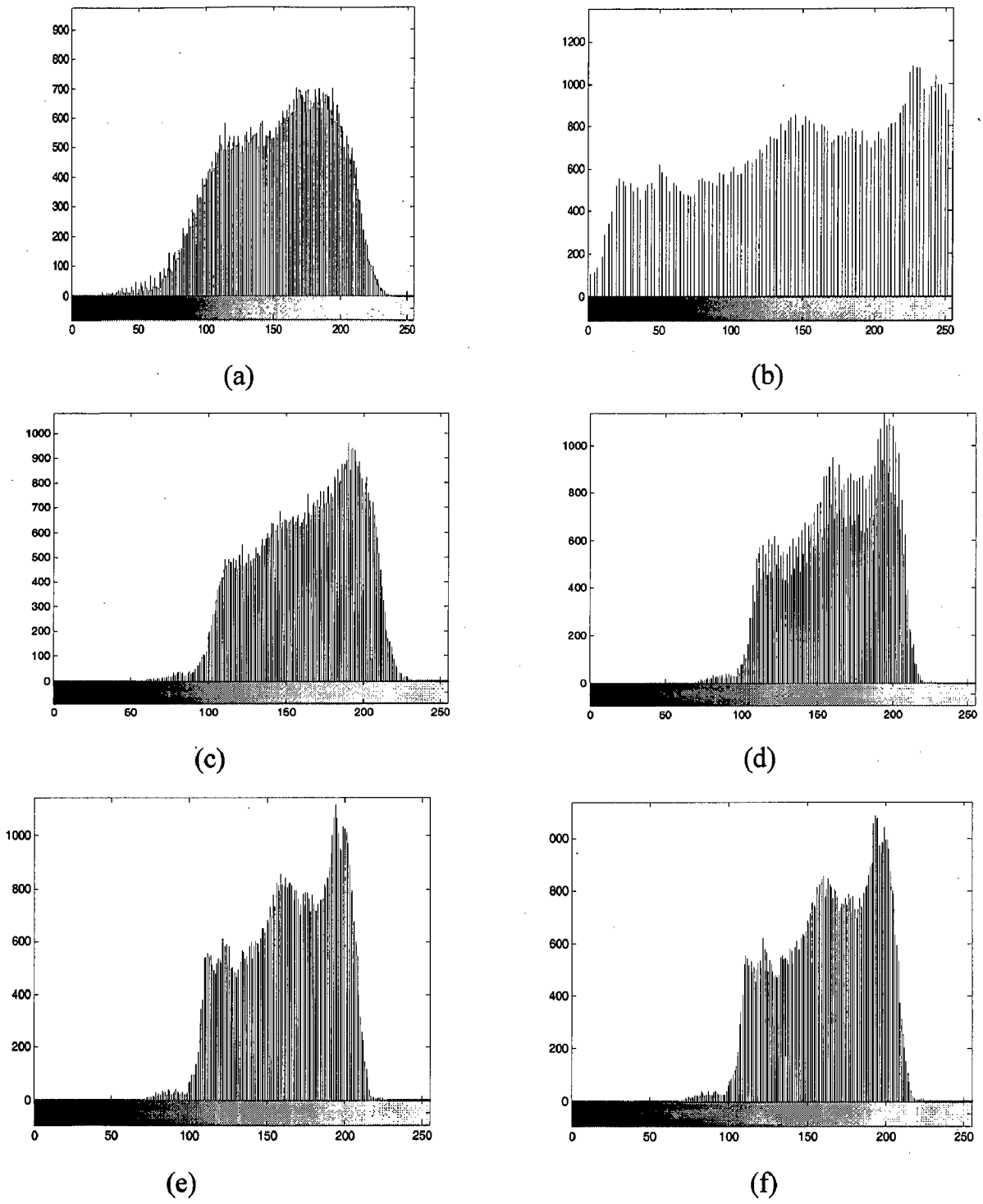


Fig-6.14- Gray level distributions (mdb209): (a) Original Image (b) image enhanced with CS (c) image enhanced with CLAHE (d)image enhanced with UM(e)image enhanced with WL(f) image enhanced with ME.

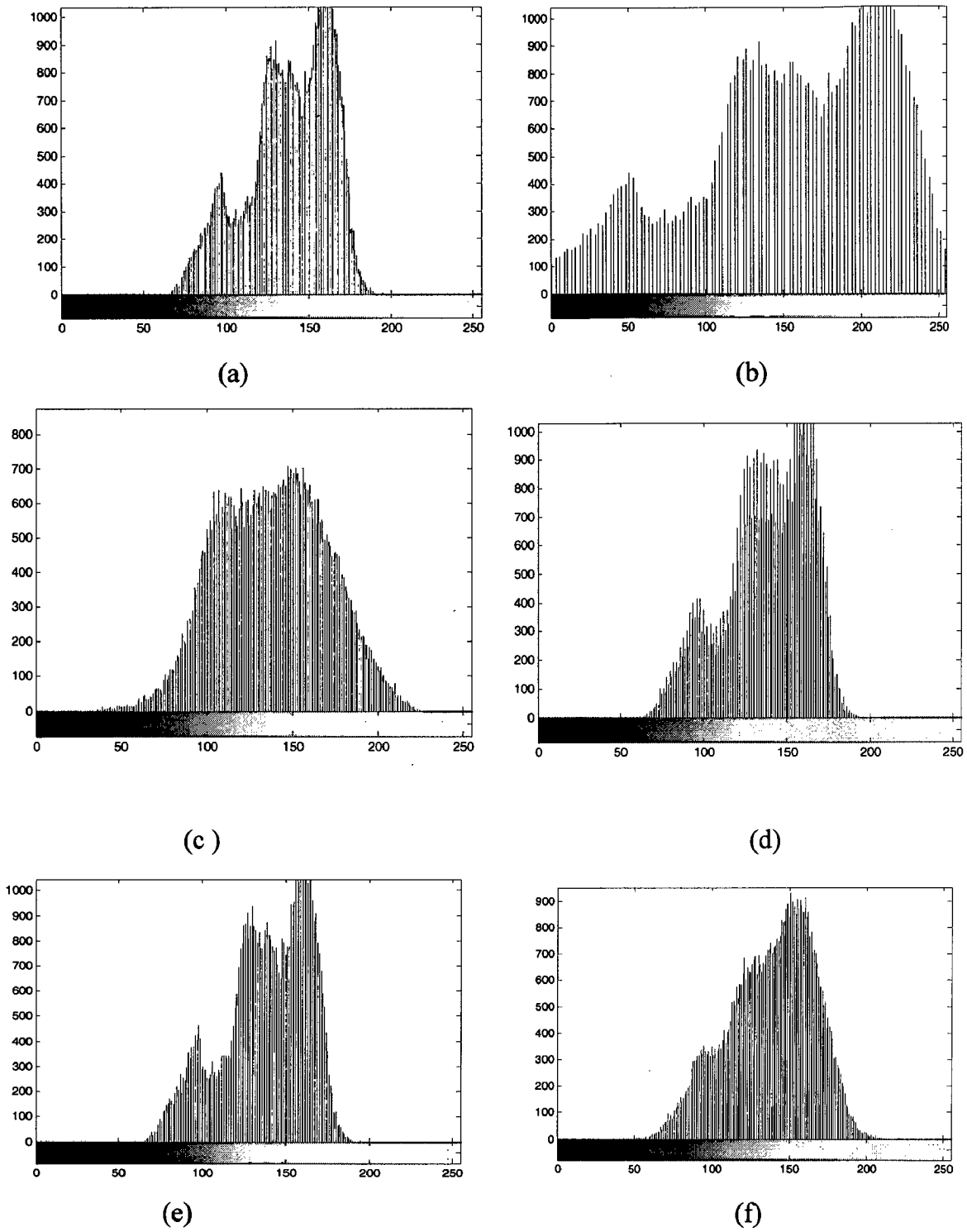


Fig-6.15- Gray level distributions (mdb213): (a) Original Image (b) image enhanced with CS (c) image enhanced with CLAHE (d)image enhanced with UM(e)image enhanced with WL(f) image enhanced with ME.

It can be seen that ME, UM and CLAHE methods compresses the highest frequencies to lie around the mean whereas CS method stretches the histogram. But the ME gave better histogram compression as compared to other methods.

Finally, it can be concluded that the ME method gives better results than the two conventional enhancement methods, namely contrast stretching(CS), contrast limited adaptive histogram equalization (CLAHE), unsharp masking (UM),wavelet based sub-band filtering technique (WL) and morphological enhancement (ME) in terms of cumulative contrast measure (D index), detail variance (DV), and background variance (BV). The superiority of ME method is further strengthened by the results of direct visual inspection, image histograms and image profiles. The gratifying results of evaluation and computational simplicity of the proposed morphological enhancement technique suggest that it can be can be used routinely in computer-assisted diagnosis of breast diseases in clinical environment.

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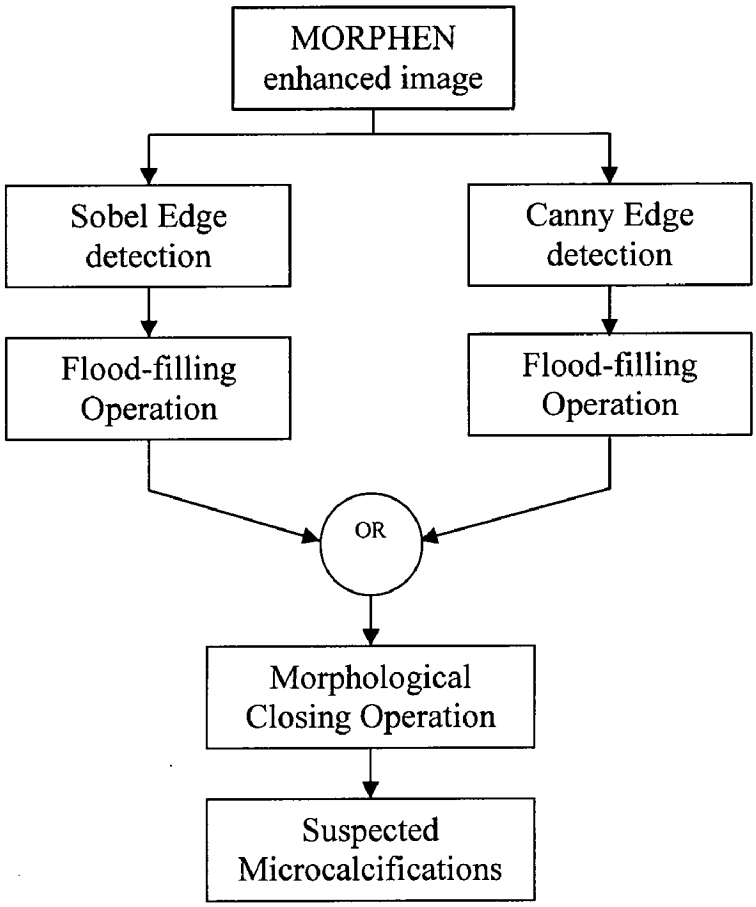

Fig-7.1- Block diagram for detection of suspected microcalcifications from enhanced mammogram ROI.

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The Canny edge detector finds edges by looking for local maximum of the gradient of unprocessed input image. In each edge detection algorithm, the gradient is

calculated using the derivative of a Gaussian filter [14], and the output is a binary image, where 1 represents edges and 0 represents background.

The Sobel and Canny binary output images are further subjected to the flood-filling operation to fill all objects with closed borders. Both flood-filled images are then logically ORed together to produce a new image that possibly includes false positives but discourages false negatives. Finally, morphological closing is applied on this new image to eliminate noise. *Fig-7.2 and 7.3*, below shows the result of morphological detection as applied to mammograms (biopsy proven cases) containing microcalcifications.

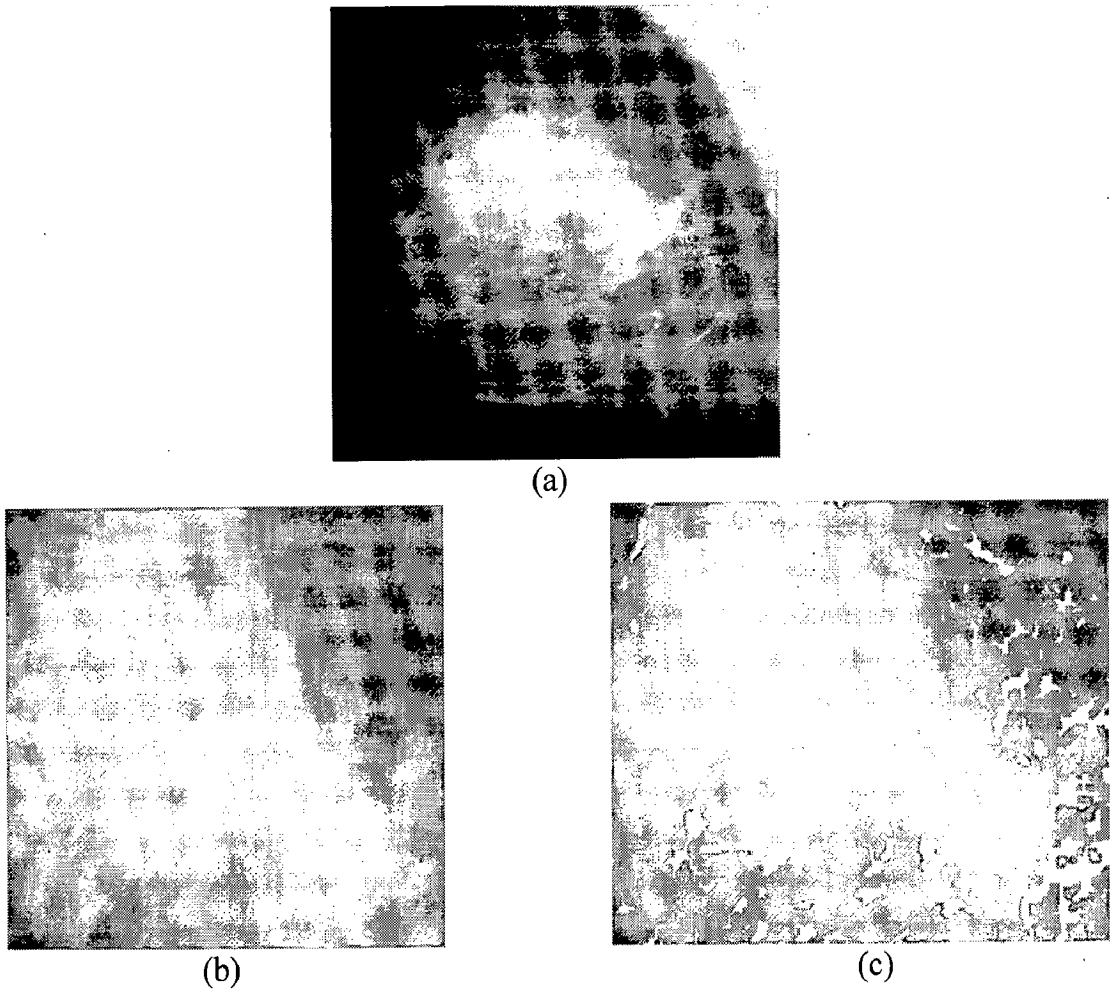
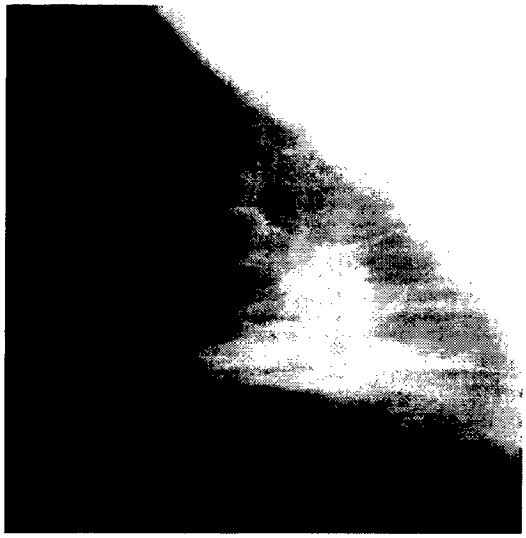
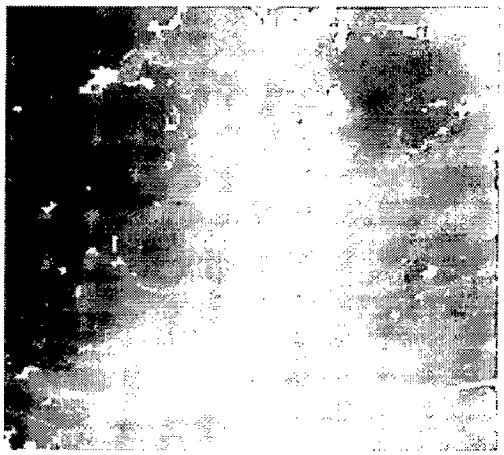


Fig-7.2-(a) Original Image (mdb209)[2] (b)ROI image (c) Image with detected MCC's



(a)

(b)



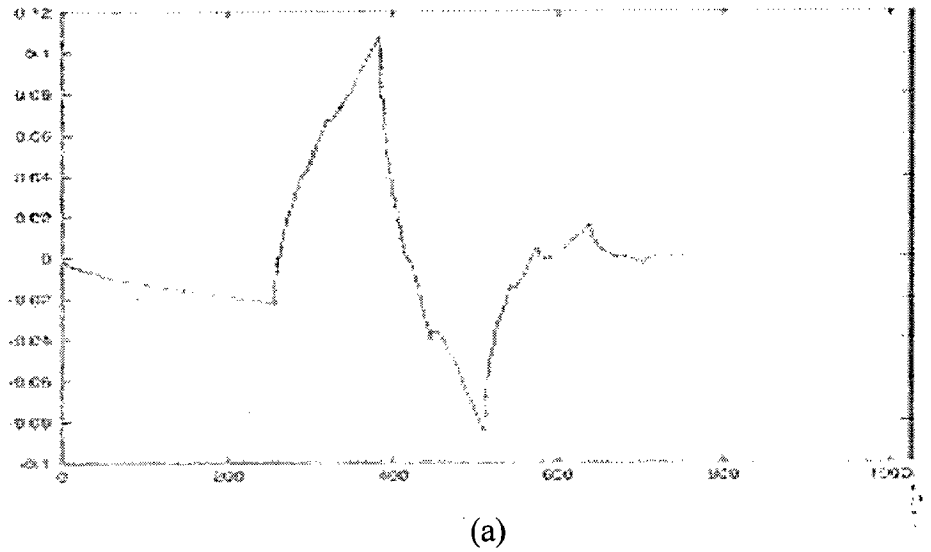
(c)

Fig-7.3- (a) Original Image (mdb213)[2] (b)ROI image (c) Image with detected MCC's

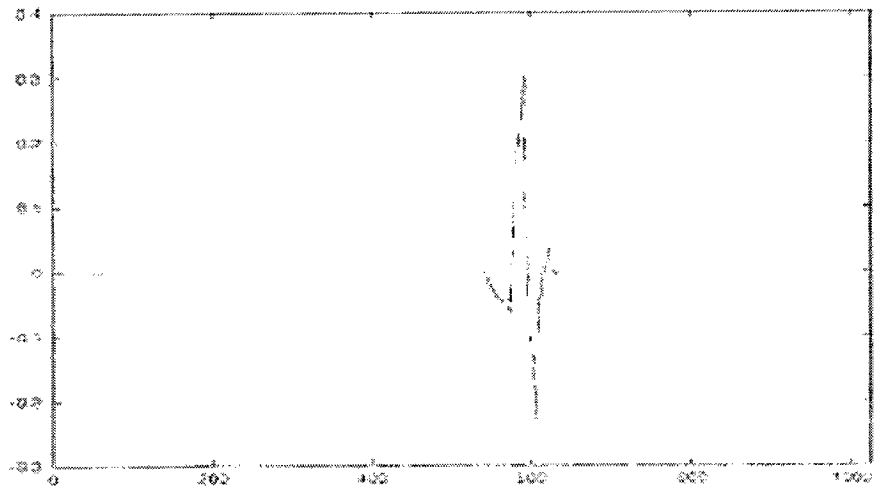
7.2 Detection Using Wavelets

Detection of microcalcifications can be achieved by employing wavelet based sub band image decomposition. The microcalcifications appear with in small clusters of few pixels with relatively high intensity compared with the neighboring pixels. Given that the microcalcifications correspond to high frequency components of the image spectrum, detection of microcalcifications is achieved by decomposing the mammogram into different frequency sub bands, suppressing the low frequency sub band and finally, reconstructing the mammogram from the sub bands containing only high frequencies [44].

According to *Fig-7.4 and 7.5*, the mother wavelet of the DAUB 4 filter is more "spike like" compared with that of smoother DAUB 20 filter. The pixels detected may belong to micro-calcifications, or background noise. Thus shorter wavelet filters are more sensitive to existing micro-calcifications but they tend to produce more false positive (FP)[8].

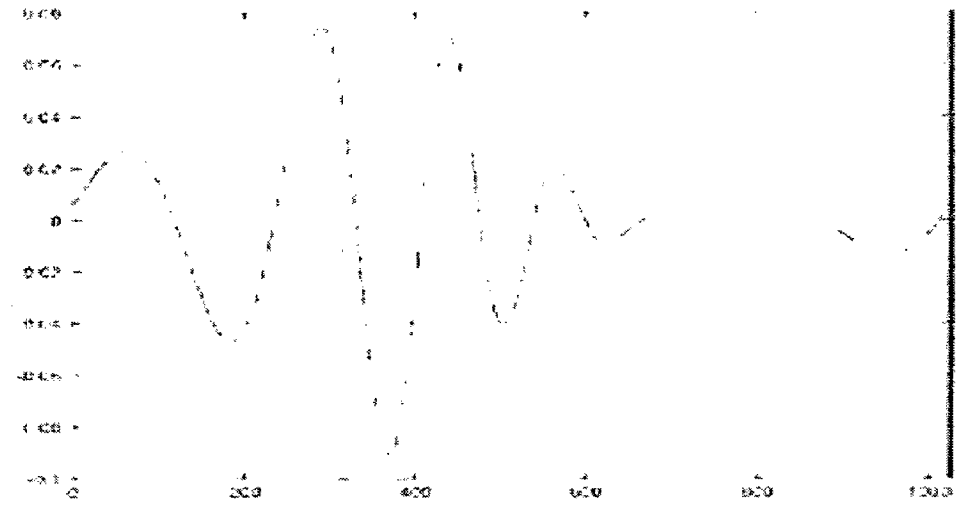


(a)

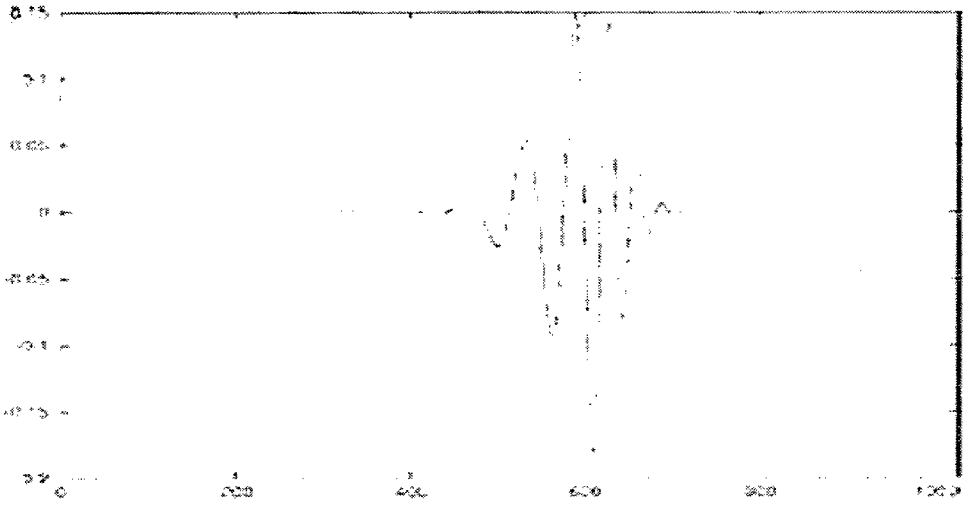


(b)

Fig-7.4- The Mother Wavelet of DB4 Wavelets; a) A wide and short wavelet for analyzing low frequency characteristics b) A narrow and tall wavelet for analyzing high frequency characteristics.



(a)



(b)

Fig-7.5- The Mother Wavelet of DB20 Wavelets; a) A wide and short wavelet for analyzing low frequency characteristics b) A narrow and tall wavelet for analyzing high frequency characteristics.

Fig-7.4 shows the amplitude plot of the mother wavelet for the family of DAUB 4 filters. *Fig-7.4(a)* represents the "long window" used to analyze long-term behavior of a signal; whereas *Fig-7.4(b)* is the scaled and translated version of the same wavelet used to analyze the instantaneous behavior of a signal. *Fig-7.5* shows the amplitude plot of the mother wavelet for the family of DAUB 20 filters[8].

Figs-7.6 and 7.7 below shows the images obtained after processing the original mammogram using DAUB 4 and DAUB 20 filters, respectively.

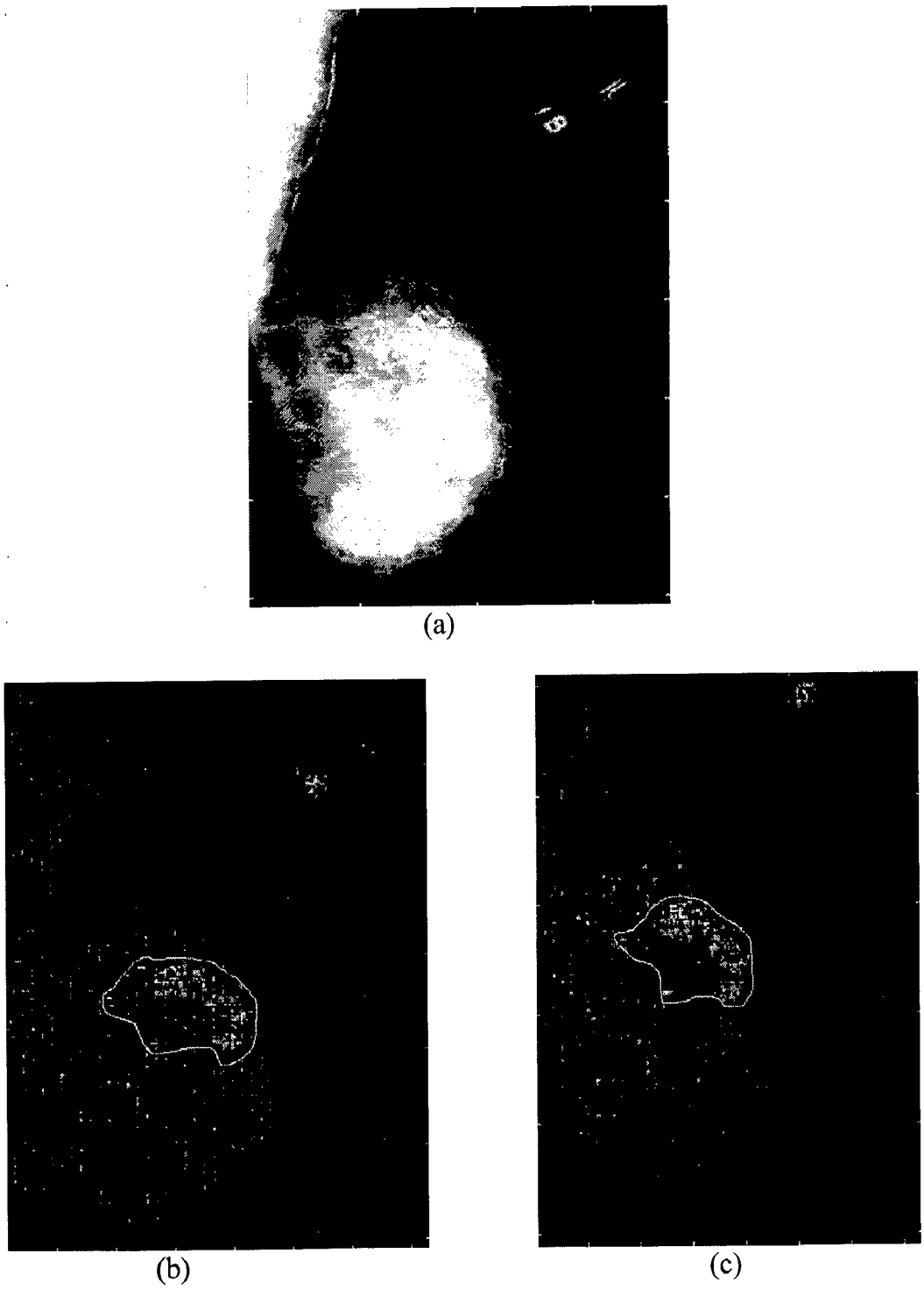
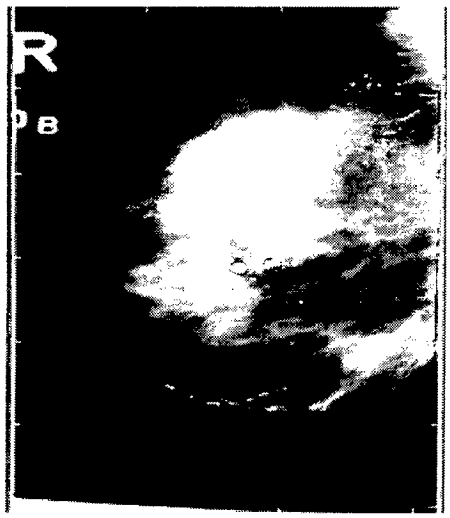
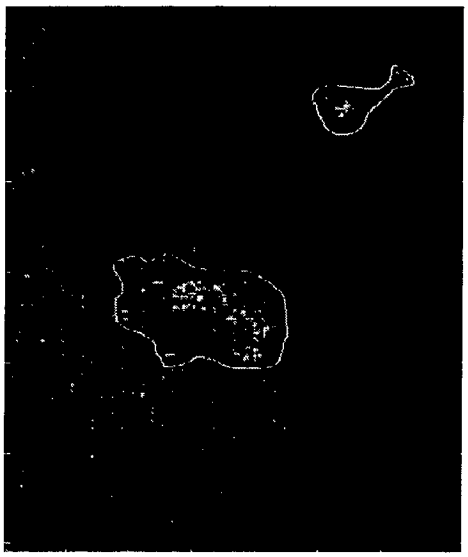


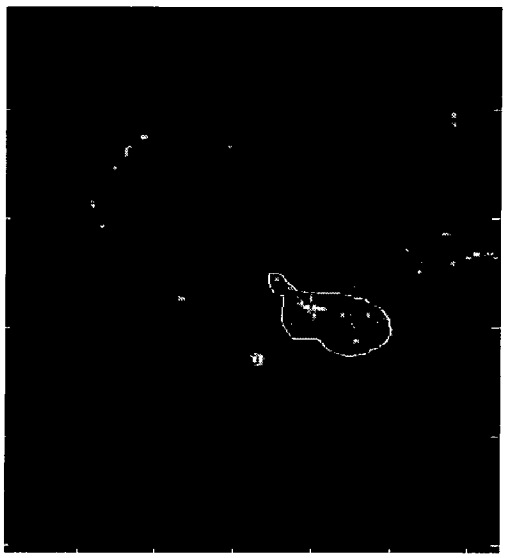
Fig-7.6- (a) Original Image –Case49.jpg Source Mcgill- database[41] (b) Diagonal detail coefficient at level 2 db-4 wavelet (c) Diagonal detail coefficient at level 2 db-20 wavelet.



(a)



(b)



(c)

Fig-7.7- (a) Original Image –Case27.jpg Source Mcgill- database[41](b) Diagonal detail coefficient at level 2 db-4 wavelet (c) Diagonal detail coefficient at level 2 db-20 wavelet

From Fig-7.6 and 7.7 it can be seen that DB-4 wavelet gives better results as compared to DB-20 wavelet. Thus shorter wavelet filters are more sensitive to existing micro-calcifications.

Regarding, morphological detection the final image possibly includes false positives but discourages false negatives. The performance can further be improved by an appropriate design of the closing filter.

Chapter 8

Results and Conclusions

Introduction- In this chapter, results obtained at different stages of the work done in the area of "medical image analysis for disease diagnosis" are elaborated. The Conclusions are drawn and future directions in which work can be continued is proposed.

The performance of morphological based processing and wavelet based processing over other enhancement algorithms has to be verified. The verification is achieved by the following two approaches.

Approach 1- Obtaining different quantitative measures for evaluation of various image enhancement techniques.

Approach 2- Obtaining the feedback from a radiologist having expertise in reading mammograms.

The different mammogram image data sources used are given below-

Resource	URL/Description
MIAS database	Mammographic Image Analysis Society Mini-mammographic database. Organizer: J Suckling, Truth-Data: C R M Boggis http://skye.icr.ac.uk/miasdb/miasdb.html
Mc-Gill database	http://sprojects.mmi.mcgill.ca/mammography/

The Task- To detect microcalcifications in digital mammograms.

Considering the fact that the characteristics of microcalcifications vary widely and they are present in extremely dense, heterogeneous parenchymal tissue it is concluded that to find clusters of microcalcifications is a difficult but challenging task.

8.1 Image Preprocessing and Enhancement-

The original raw images were cropped to obtain the region of interest. The ROI's were processed by different image enhancement algorithms , like histogram equalization , contrast limited adaptive histogram equalization, contrast stretching, unsharp masking , pseudo coloring, Wavelet based sub-band filtering technique(WL) and morphological enhancement.

Approach 1- Nine sample images selected at random from MIAS database were used and the results of different enhancement algorithms were compared by finding quantitative measures such as DV/BV (Detail Variance/ Background Variance) ratio and D-Index.

Since the DV/BV ratio is based on a single statistical parameter i.e. variance and D-Index is the only index available in literature which uses both the standard deviation and entropy of the image. So it can be concluded that D-Index is best to quantitatively rank enhancement techniques for a particular image. *Fig-8.1* below shows the D-Index profile for different enhancement algorithms.

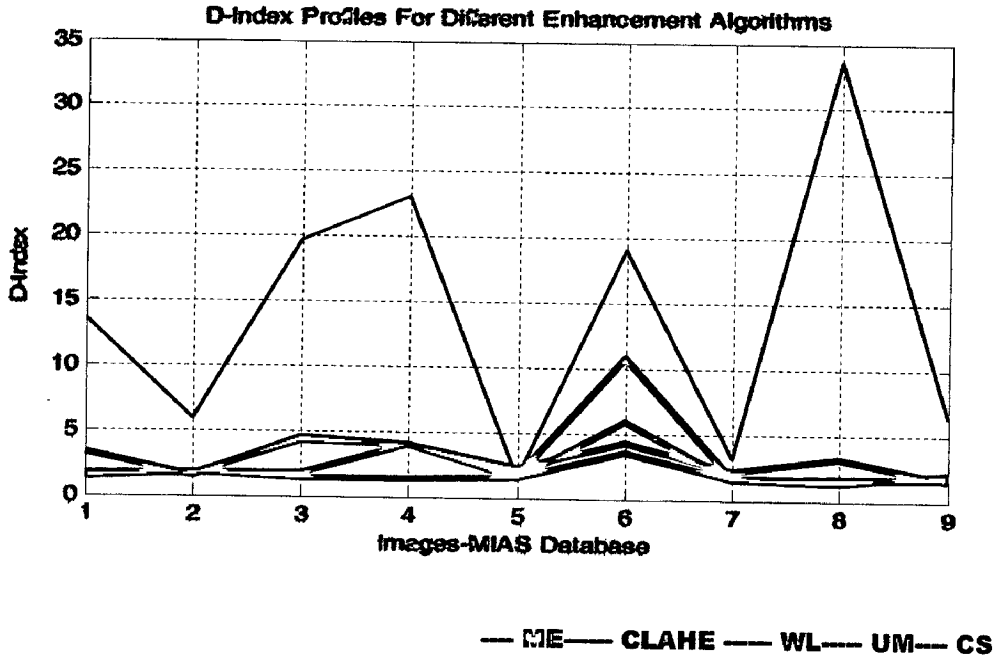


Fig-8.1 D-index profile for different enhancement algorithms

From the D-index profiles as shown above in *Fig-8.1*, it can be concluded that lowest value of D-index is obtained from morphological enhancement. The second lowest values for D-index are obtained by wavelet based sub band filtering technique.

It can be therefore concluded that wavelet based sub-band filtering technique is a general method which will work equally well for all images because, it is inhibiting noise and not enhancing the ROI , but due to noise inhibition the contrast improvement is obvious. The method is good because it is not distorting the image that is noise inhibition is achieved without any loss of diagnostic information.

So it can be concluded that although Wavelet based sub band filtering technique is better for all medical images, but for mammograms where, enhancement of microcalcifiaction clusters is the ultimate goal morphological enhancement is ideally suited.

This fact is further strengthened by finding out DV/BV ratio for various enhancement algorithms for nine different images selected at random from MIAS data base. It may be noted that larger the DV/BV ratio better is the enhancement. *Fig-8.2* below, shows the profile for DV/BV ratio for different enhancement algorithms.

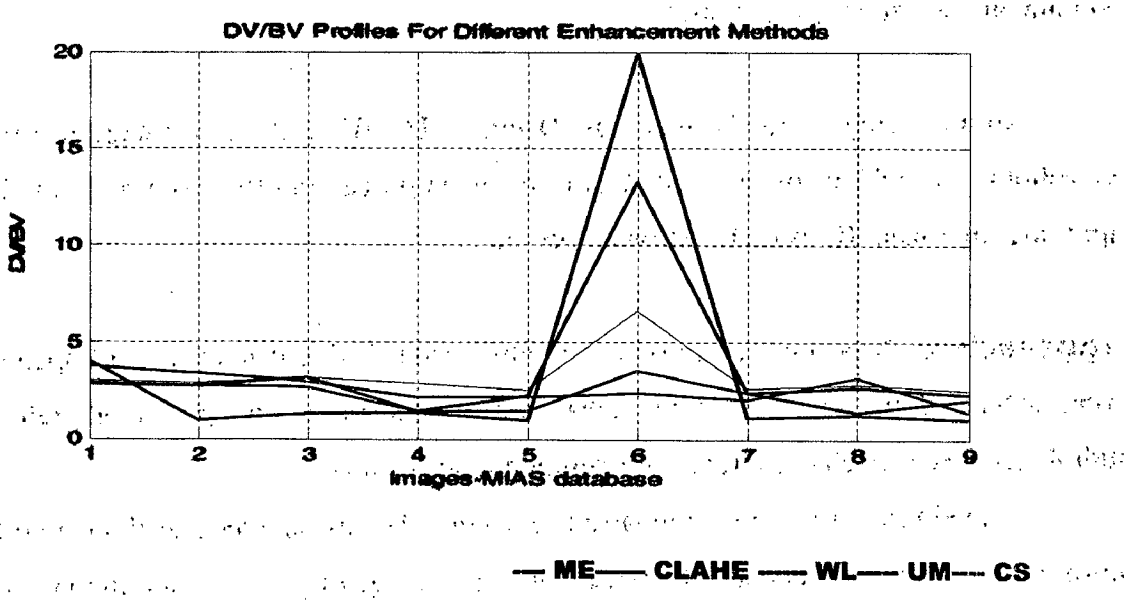


Fig-8.2 DV/BV ratio profile for different enhancement algorithms

. The performance of Morphological enhancement was further strengthened by obtaining the image profile across a line containing calcifications spot. *Fig-8.3* below, shows image profiles for different enhancement algorithms.

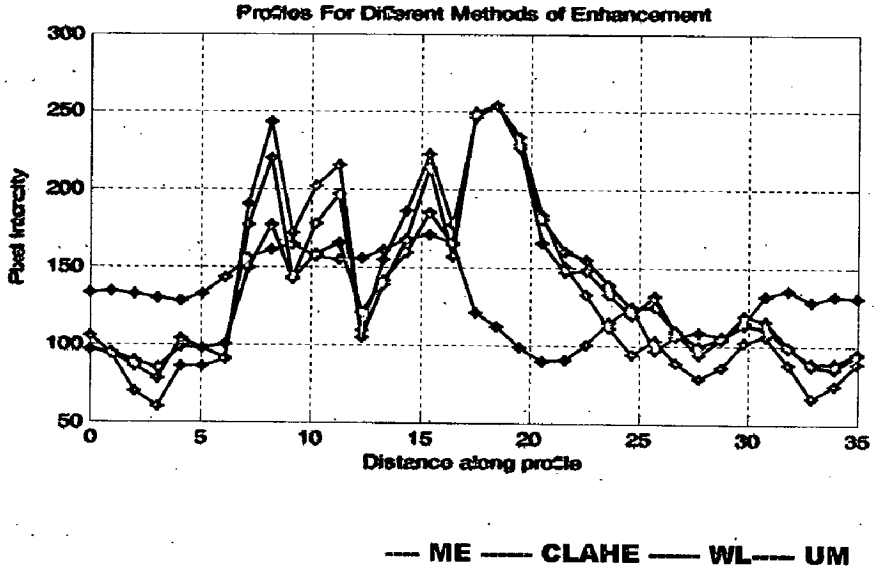


Fig-8.3 Image profiles for different enhancement algorithms

As shown in figure above Profile obtained by ME enhancement method shows smoother transition in gray scales thus it indicates that profile obtained by ME method doesn't contain any spurious spikes (valleys).

So according to all the methods, D-Index, DV/BV ratio and image profiles the Morphological enhancement is rated as best for preprocessing the mammograms before applying microcalcification detection algorithms.

Approach 2- Nine images chosen randomly from different databases (Appendix-A) were enhanced by seven different enhancement algorithms and presented before the radiologist having rich experience in reading mammograms.

A feedback form –questionnaire (Appendix-B) was designed to illicit maximum information about the enhanced images, like image quality rating, additional clinical information obtained loss of any clinical information, and number of additional microcalcifications visible after enhancement.

Feedback obtained from the radiologist, varied considerably for images from different database's as the performance of the enhancement algorithm depends upon quality of the raw images.

For Images from MIAS database- The radiologist rated morphological enhancement as a good method for enhancing mammograms in 100% of the cases and wavelet based sub band filtering technique is rated as good for 66.6% of the cases.

For Images from Mc-gill database- The radiologist rated both morphological enhancement and wavelet based sub band filtering technique as good for 75.0% of the cases.

Our comparison with Approach 1 also matches with the radiologist feedback. As a result it can be concluded that morphological enhancement is best suited for enhancement of microcalcifications in mammograms.

The structuring element used for constructing opening and closing filters to perform morphological enhancement reveals more number of calcifications then which can be seen in original ROI image, without distorting the background parenchymal tissue.

Wavelet based sub-band filtering also produces some desirable results , as it inhibits noise and retain the boundary information so it can be concluded that sub-band filtering holds promise for enhancement of any kind of medical image, but results for mammograms are better with morphological enhancement.

8.2 Microcalcification Detection

Both Morphological based processing and Wavelet based processing are used for calcification detection.

Regarding morphological based processing the performance is dependent upon the choice of the structuring element used for constructing opening and closing filters.

The resulting image obtained after morphological based processing possibly includes false positives but discourages false negatives. So it can be concluded that a closing operation (for image smoothing), with a suitable structuring element can further improve our results.

Regarding detection of calcifications by WL processing studies indicate that both DB-4 and DB-20 wavelet have been used to detect microcalcifiactions. Since microcalcifications are defined as being less than 500μm, the forward wavelet transform of the mammogram is computed containing enough levels to encompass the size range-two levels in our implementation. Incomplete reconstruction is performed from only those wavelet coefficients in which microcalcifications are present, namely high pass sub-bands of the second level.

Experiments have shown that above level 3 calcifications are not represented and level one contains mostly noise. The reconstructed image highlights the suspicious area. it is observed that, DB-4 wavelet gives better results as compared to DB-20 wavelet. Therefore it can be concluded that shorter wavelet filters are more sensitive to existing micro-calcifications.

8.3 Future Directions-

The Proposed CAD based system is as shown in *Fig-8.4* below.

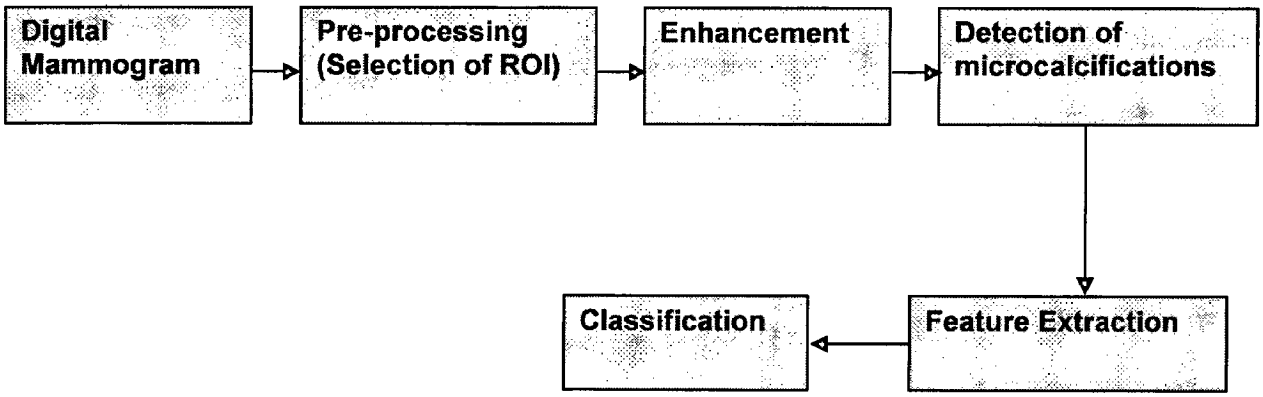


Fig-8.4 Proposed CAD system

Developing modules for feature extraction and classification stage are future directions in this area to develop a fully automated CAD based system for disease diagnosis.

The desire to use computers in place of second radiologist, or as a pre-screener to separate out clearly normal mammograms, is the motivations for computer aided detection research.

Appendix-A

Mammogram Image Data Sources

Resource	URL/Description
MIAS database	Mammographic Image Analysis Society Mini-mammographic database. Organizer: J Suckling, Truth-Data: C R M Boggis http://skye.icr.ac.uk/miasdb/miasdb.html
Mc-Gill database	http://sprojects.mmi.mcgill.ca/mammography/

Appendix-B

Feedback Form For Radiologist Feedback

Image Details	File Name- mdb209.pgm					File Source- MIAS database		
Method used	Image Quality					Additional clinical Information (Y/N)	Loss of clinical Information (Y/N)	No. of MCC's
	P	F	G	VG	E			
CS								
UM								
UM+CS								
ME								
ME+CS								
WL								
CLAHE								
Remarks								
Reported By- Dr. Vivek Gupta , Consultant-Radiologist, Department of Radio-Diagnosis and Imaging, PGIMER, Chandigarh								

The enhanced images were compared with the output from Dicom-Viewer Software used in digital mammography lab PGIMER, chandigarh.

Appendix-C

Publications From The Work Done

Jitendra Virmani, Sukwinder Singh, Vinod Kumar, "Statistical based sub band filtering technique for enhancement of digital mammograms", Proc. National conference on computational intelligence in electrical engineering, SLIET, Longowal, Punjab (INDIA). November 18-19, 2005. pp. [29-32].

Jitendra Virmani, Sukwinder Singh, Vinod Kumar, "Quantitative measures for evaluation of mammographic image contrast enhancement techniques", Proc. National conference on information and emerging technologies , IET, Bhaddal, Punjab (INDIA). Feb 17-18, 2006. pp.[17-22].

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