Early Detection of Breast Cancer using linear Adaptive filters and calcium count in mammograms

ER. SHATANJAY MISHRA, ER. PAVAN KUMAR

Research Scholar, Assistant professor
DEPARTMENT OF ELECTRONICS ENGINEERING,
MAHARISHI UNIVERSITY OF INFORMATION & TECHNOLOGY, LUCKNOW, INDIA

Abstract: Breast cancer is one of the leading causes to women mortality in the world. Primary prevention is not possible since the cause of this disease is still not understood. However, existing methods of treatment are very effective against breast cancer in its early phase when the balance between the tumor and its host is more favorable. Therefore, removal of the cancer while it is still in its early stage is the most promising way to achieve a significant change in the current breast cancer situation using mammograms. Mammograms are among the most difficult radiological images to interpret by radiologists. Dense breasts, improper technical factors, or simple oversight by radiologists may contribute to the failure of detecting micro calcifications.

     The proposed work presents a novel approach for detection of Micro calcifications in mammograms using Nonlinear Filter. The method consists of Image Denoising using Median Filter, Image Contrast Enhancement by applying a Nonlinear Operator followed by an Edge Detection method using Co-ordinate Logic Filter. The experimental results show that the proposed method can locate Microcalcifications in an efficient way.

Index Terms – **filters for region of interest, histogram, Equalizer , Edge detector ,Morphology etc.**

Introduction - Breast Cancer is one of the most deadly diseases for women. It is a leading cause of fatality among all cancers for women in the 35 to 55 age group, also with relevant number of cases for women younger than 35. Primary prevention is not possible since the cause of this disease is still not understood. However, current methods of treatment are very effective against breast cancer in its early phase when the balance between the tumor and its host is more favorable. Therefore, removal of the cancer while it is still in its early stage is the most promising way to achieve a significant change in the current breast cancer situation. The survival rate approaches 100 percent if cancer is detected early. Mammography – breast x-ray imaging – is the most effective, low cost, and reliable method that is used in the early detection of breast cancer. Microcalcifications are considered to be important signs of breast cancer, they appear as bright spots of calcium deposits. It has been reported that 30–50% of breast cancers detected radiographically demonstrate microcalcifications on mammograms, and 60–80% of breast carcinomas reveal microcalcifications upon histologic examinations. The high correlation between the presence of microcalcifications and the presence of breast cancers indicates that accurate detection of microcalcifications will improve the efficacy of mammography as a diagnostic procedure. The task of detection of microcalcifications for the diagnosis of breast cancer is a difficult one. Mammograms are among the most difficult radiological images to interpret by radiologists. Dense breasts, improper technical factors, or simple oversight by radiologists may contribute to the failure of detecting microcalcifications.

1.1 Types Of Abnormalities

     A mass is defined as a space-occupying lesion seen in more than one projection. A mass is usually characterized by its shape and margin. Generally speaking, a mass with a regular shape has a higher probability of being benign, whereas a mass with an irregular shape has a higher probability of being malignant. Most of the mass detection algorithms are composed of two stages:
1) Detection of suspicious regions on the mammogram and
2) Classification of suspicious regions as mass or normal tissue.
The algorithms for the first stage in mass detection are generally pixel-based or region-based. There are several types of abnormalities present in mammographic images and they are categorized as:
- Microcalcification.
- Circumscribed masses.
- Speculated masses.
- Asymmetry.

1.1.1 Microcalcification

     Microcalcifications are considered to be important signs of breast cancer, they appear as bright spots of calcium deposits. It has been reported that 30–50% of breast cancers detected radiographically demonstrate microcalcifications on mammograms, and 60–80% of breast carcinomas reveal microcalcifications upon histologic examinations. The high correlation between the presence of microcalcifications and the presence of breast cancers indicates that accurate detection of microcalcifications will improve the efficacy of mammography as a diagnostic procedure. The task of detection of microcalcifications for the diagnosis of breast cancer is a difficult one. Mammograms are among the most difficult radiological images to interpret by radiologists. Dense breasts, improper technical factors, or simple oversight by radiologists may contribute to the failure of detecting micro calcifications

2. Literature Review

     Many techniques have been proposed to detect the presence of MCs in mammograms: Image enhancement techniques, ANN, Wavelets Analysis, Support Vector Machines (SVM), Mathematical Morphology, Bayesian Image analysis models, High

Order Statistic, Fuzzy Logic, etc. Image enhancement algorithms have been utilized for the improvement of contrast features and the suppression of noise.

➢ Papadopoulos, D.I. Fotiadis, and L. Costaridou in the paper '**Improvement of microcalcification cluster detection in mammography utilizing image enhancement techniques**' published in 2008 proposed five image enhancement algorithms for the detection of MCs in mammograms which are contrast-limited adaptive histogram equalization (CLAHE), the local range modification (LRM), 2-D redundant dyadic wavelet transforms (RDWT), RDWT linear stretching (WLST) and wavelet shrinkage (WSRK) techniques.

➢ Yuan. Wu, Q. Huang, Y. Peng, and W. Situ in the paper '**Detection of microcalcifications in digital mammograms based on dual-threshold**' published in 2006 proposed an approach for detecting MCs employing a dual-threshold and LoG edge detection method. Wavelets have been also employed in MCs detection providing high spatial frequency features in mammograms. M. Bhattacharya and A. Das in the paper '**Fuzzy logic based segmentation of microcalcification in breast using digital mammograms considering multiresolution**' proposed in the journal **Machine Vision and Image Processing Conferenc**e, 2007 a method based on discrete wavelet transform due to its multiresolution properties with the goal to segment MCs in digital mammograms. Morphological Tophat algorithm was applied for contrast enhancement of the MCs.

➢ G. Veni, E.E. Regentova, and L. Zhang in the paper '**Detection of clustered microcalcifications with susan edge detector, adaptive contrast thresholding and spatial filters** 'proposed in 2008 ,a method based in SUSAN edge detector and adaptive contrast thresholding technique and spatial filters for detection of MCs.

Proposed Work

➢ The proposed work presents a novel approach for detection of Microcalcifications in mammograms using Nonlinear Filters. The method consists of Image Denoising using Median Filter, Image Contrast Enhancemen*t* by applying a Nonlinear Operator followed by an Edge Detection method using Coordinate Logic Filter and Morphological Filter. The experimental results obtained from MATLAB 7.6 show that the proposed method can locate microcalcifications in an efficient way.

➢ In the first stage, many ROIs are selected from the mammograms and are resized; next, in the second stage we apply a Median Filter for Image Denoising of the ROI images. The median filter is used to ensure that any unwanted structures are eliminated from the image.

➢ In the next block, we apply an Image Contrast Enhancement by applying a Nonlinear Operator. The high bright values in the ROI image are enhanced and the low bright values are diminished.. This technique suppresses pixel value of very small amplitude and enhances only those pixels that are larger than determined threshold within each level of transform space.

➢ Next to this, an Edge Detector involving Morphological Filters as well as Coordinate Logic Filter is used. Both the techniques constitute a powerful set of tools for extracting feature of interest in an image. It can be used as the basis for developing image segmentation procedures with a wide range of applications.

➢ Various parameters are used to determine the quality of an image at various stages. The few parameters used in our approach are PSNR, Quality factors and Edge Similarity index. PSNR is used for determining the peak signal to noise ratio of the denoised image. Quality factor calculates the quality of contrast enhanced image while Edge Similarity index is used for computing the quality of edge detected image.

➢ Our proposed approach aims at the improvement of the system performance in the detection of MCCs in ROI image that could be missed or misinterpreted by medical experts. Edge detection is a fundamental and essential processing step. In case of mammograms it presents a good performance for MCCs detection. The edge of MCs is a very important feature to determine the malignancy of MCs. For these reason, in this paper, we have proposed a novel method for the detection of MCCs using image enhancement and morphological filters. Finally, computer simulations demonstrated that our method can locate MCCs in mammograms satisfactorily and evaluated of visual way.

3. A Survey of Various Cad Techniques Used For Breast Cancer Detection

Important technical improvements have been made to X-ray equipment in the past years, namely with the generalized adoption of digital technologies, thus providing better and higher resolution images. Also, considerable research has been carried in image analysis techniques and methods to assist radiologists in the identification of abnormalities.

Among these techniques one has to mention image and contrast enhancement, mathematical morphology and wavelet based methods, or combinations of these methods. The focus has been on wavelet-based image analysis and contrast enhancement to make image features more visible, to assist radiologists on the interpretation of malignant masses and microcalcifications.

Due to mammographic image characteristics one needs image analysis tools that can increase image contrast of its features and well localized decomposition schemes. The main objective is to make high frequency features more visible, thus facilitating image interpretation.

The main difficulty in dealing with biomedical objects is the extreme variability of the signals and the necessity to operate on a case by case basis. For example, it is frequently the deviation of some signal feature from the normal that is the most relevant information for diagnosis. As a result, the problems tend to be less well defined than those in engineering and the emphasis is more on designing robust methods that work in most circumstances, rather than procedures that are optimal under very specific assumptions.

3.1 Wavelets And Wavelet Transform

In the past few years, researchers in applied mathematics and signal processing had developed powerful wavelet methods for the multiscale representation and analysis of signals. These new tools differ from the traditional Fourier techniques by the way in which they localize the information in the time-frequency plane; in particular, they are capable of trading one type of resolution for the other, which makes them especially suitable for the analysis of non stationary signals.

One privileged area of applications where these properties have been found to be relevant is biomedical engineering. Due to the wide variety of signals and problems encountered in medicine and biology, the spectrum of applications of the wavelet transform (WT) has been extremely large. It ranges from the analysis of the more traditional physiological signals such as the electrocardiogram (ECG), to the very recent imaging modalities including positron emission tomography (PET) and magnetic resonance imaging (MRI).

Another important aspect of biomedical signals is that the information of interest is often a combination of features that are well localized temporally or spatially (e.g., spikes and transients in electroencephalograph (EEG) signals and microcalcifications in mammograms) and others that are more diffuse (e.g., small oscillations, bursts, and texture). This requires the use of analysis methods sufficiently versatile to handle events that can be at opposite extremes in terms of their time-frequency localization.

Due to mammographic image characteristics one needs image analysis tools that can increase image contrast of its features and well localized decomposition schemes. The main objective is to make high frequency features more visible, thus facilitating image interpretation. In signal analysis, a signal $f(t)$ is represented as a weighted sum of building blocks of basis functions

$$f(t) = \sum_k c_k \psi_k(t)$$

where ψ_k are basis functions and c_k are weight coefficients. Since the basis functions are fixed, the information about the signal is carried by the coefficients. Choosing sinusoids as the basis functions equation below yields the Fourier representation. To detect spikes or well localized high frequency components in the signal, one needs a representation which contains information about both, the time and frequency behavior of the signal.

However, resolution in time (Δt) and resolution in frequency $(\Delta \omega)$ cannot be arbitrarily small at the same time as their product is lower bounded by the uncertainty principle

$$\Delta t \cdot \Delta \omega \geq \tfrac{1}{2}$$

This means that one must trade off time resolution for frequency resolution, or vice versa. However, low-frequency events are usually spread in time (non local) and high frequency events are usually concentrated (localized) in time. Therefore, it is possible to obtain good time-frequency information of a signal by choosing the basis functions to act as cascaded octave band-pass filters which repeatedly split the bandwidth of the signal in half. On the other hand sinusoids cannot provide information about the time behavior of a signal as they have infinite support. The solution is to use basis functions that have finite (compact) support and different widths.

Beside the growing number of researchers and the rate of publication that keeps on increasing steadily, there are other indicators of the current popularity of wavelets in biomedical engineering.

For a wavelet representation, the set of basis functions ψ_k are scaled and translated versions of the same prototype function $\psi(t)$ known as *mother wavelet*. Scaling is achieved by multiplying t by a scale factor, normally a power of two, $\psi(2^a t)$, $a \in \mathsf{Z}$. Since the prototype function has finite support, it can be scaled and translated to cover the all signal *i.e.* $\psi(2^a t - b)$, $b \in \mathsf{Z}$. The wavelet decomposition of a signal can be represented as

$$f(t) = \sum_a \sum_b c_{ab} \psi_{ab}(t)$$

where $\psi_{ab}(t) = 2^{a/2} \psi(2^a t - b)$ and c_{ab} are coefficients that can be computed via the wavelet transform.

The wavelet transform of a signal $x(t)$ is defined as

$$W_x(a,b) = \frac{1}{\sqrt{a}} \int_{\mathsf{R}} x(t)\psi^*\left(\frac{t-b}{a}\right) dt$$

The discrete wavelet transform (DWT) is obtained by taking the discrete values of the scale and translation parameters

$$w_{k,j} = W_x(2^{-j}, k2^{-j}) = \frac{1}{\sqrt{2^{-j}}} \int_{\mathsf{R}} x(t)\psi^*\left(\frac{t-k2^{-j}}{2^{-j}}\right) dt$$

Wavelets analysis has good scale-frequency and localization properties, allows the decomposition of signals with different levels of detail and also other interesting properties, namely:

- **Discrete Transform**: The DWT has relevant advantages for practical implementations;
- **Multiresolution**: The DWT can be implemented in filter banks;
- **Flexibility and Robustness**: The discrete transform is also applicable to images, being flexible with respect to image resolution and robust to image quality;
- **Invertibility**: It is possible to reconstruct the image from DWT coefficients by computing its inverse transform.

4. Image Enhancement Techniques

4.1 Introduction

The principal objective of enhancement is to process an image so that the result is more suitable than the original image. Image enhancement approaches fall into two broad categories: spatial domain methods and frequency domain methods. The term

spatial domain refers to the image plane itself, and approaches in this category are based on direct manipulation of pixels in an image. *Frequency domain* processing techniques are based on modifying the Fourier transform of an image. *Spatial domain* refers to the aggregate of pixels composing an image. Spatial domain methods are procedures that operate directly on these pixels. Spatial domain processes will be denoted by the expression

$$g(x, y) = T[f(x, y)]$$

where f(x, y) is the input image, g(x, y) is the processed image, and T is an operator on f, defined over some neighbourhood of (x, y). In addition, T can operate on a *set* of input images, such as performing the pixel-by-pixel sum of K images for noise reduction. The simplest form of T is when the neighbourhood is of size 1*1 (that is, a single pixel). In this case, g depends only on the value of f at (x, y), and T becomes a *gray-level* (also called an *intensity* or *mapping*) *transformation function* of the form

$$s = T(r)$$

where, for simplicity in notation, r and s are variables denoting, respectively, the gray level of f(x, y) and g(x, y) at any point (x, y).
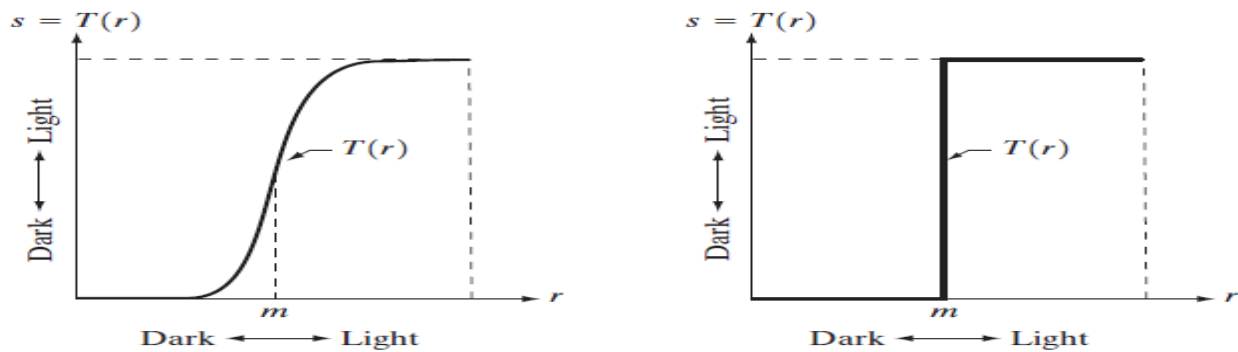
Fig.4.1: Gray level transformation functions for contrast enhancement.

4.2 Basic Gray Level Transformations

To begin with the study of image enhancement techniques first of all a brief discussion on gray-level transformation functions. These are among the simplest of all image enhancement techniques. The values of pixels, before and after processing, will be denoted by r and s, respectively. As indicated in the previous section, these values are related by an expression of the form $s=T(r)$, where T is a transformation that maps a pixel value r into a pixel value s. Since we are dealing with digital quantities, values of the transformation function typically are stored in a one-dimensional array and the mappings from r to s are implemented via table lookups. For an 8-bit environment, a lookup table containing the values of T will have 256 entries.

The three basic types of functions used frequently for gray level image enhancement are:

- Linear (negative and identity transformations),
- Logarithmic (log and inverse-log transformations), and
- Power- law (nth power and nth root transformations).

The identity function is the trivial case in which output intensities are identical to input intensities. It is included in the graph only for completeness.

Image Negatives

The negative of an image with gray levels in the range [0, L-1] is obtained by using the negative transformation which is given by the expression,
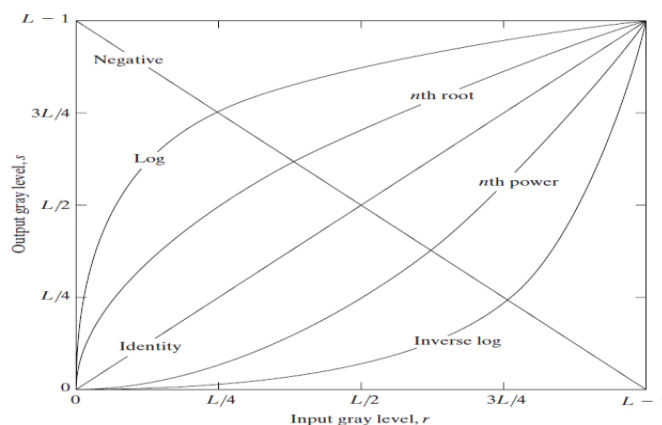
$$s = L - 1 - r.$$

Fig. 4.2: Some basic gray-level transformation functions used for image enhancement.

Reversing the intensity levels of an image in this manner produces the equivalent of a photographic negative. This type of processing is particularly suited for enhancing white or gray detail embedded in dark regions of an image, especially when the black areas are dominant in size. The original image is a digital mammogram showing a small lesion. In spite of the fact that the visual content is the same in both images, note how much easier it is to analyze the breast tissue in the negative image in this particular case.

Log Transformations

The general form of the log transformation shown below

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

Where c is a constant, and it is assumed that r >= 0. Transformation maps a narrow range of low gray-level values in the input image into a wider range of output levels. The opposite is true of higher values of input levels. We would use a transformation of this type to expand the values of dark pixels in an image while compressing the higher-level values. The opposite is true of the inverse log transformation. Any curve having the general shape of the log functions would accomplish this spreading/compressing of gray levels in an image. In fact, the power-law transformations are much more versatile for this purpose than the log transformation. However, the log function has the important characteristic that it compresses the dynamic range of images with large variations in pixel values. A classic illustration of an application in which pixel values have a large dynamic range is the Fourier spectrum. It is not unusual to encounter spectrum values that range from 0 to 10^6 or higher. While processing numbers such as these, presents no problems for a computer, image display systems generally will not be able to reproduce faithfully such a wide range of intensity values. The net effect is that a significant degree of detail will be lost in the display of a typical Fourier spectrum.

4.3 Histogram Analysis

Histogram is the graphical representation of various intensities of an image. A Histogram with a small spread has low contrast and a Histogram with a wide spread has a high contrast. An image with its Histogram clustered at the low end of the range is dark and a Histogram with the values clustered at the high end of the range corresponds to a bright image. Histogram can also be modified by mapping functions such as stretch, slide and slide. But these functions will not produce a desired result. Histogram Equalization is used to equalize the image with equal function.

The image in fig (a) is the original image. The image in fig (b) shows the Histogram of that image. As the image is lacking contrast, the intensity values are present in one side of the Histogram. So to enhance the contrast various Image Enhancement techniques are used.
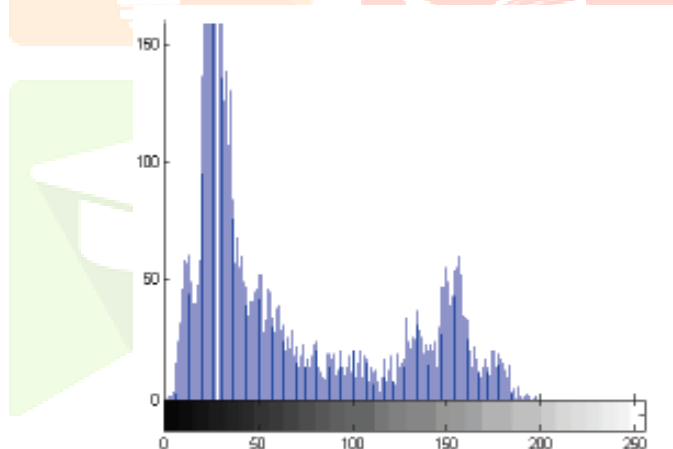

Fig.4.4(a) Original Image

(b) Histogram of the Image

4.4 Histogram Equalization

Histogram equalization is a popular technique for improving the appearance of a poor image. Its function is similar to that of a histogram stretch but provides more visually result across a wider range of images. It is a technique where the histogram of the resultant image is as flat as possible.

Fig.4.5 (a) Original Image

(b) Histogram Equalized

The Histogram Equalization process for digital images consists of four steps:
1. Finding the running sum of the histogram values.
2. Normalize the values from step 2.
3. Multiply the values from step 2 by the maximum gray values and round.
4. Map the gray-level values to the results from step 3 using a one-to-one correspondence.

Histogram Equalization is one of the Spatially Uniform Operator. In this method, transformation is applied to all the pixels of the image. As a result the image becomes over enhanced and the resultant image will be very bright. Histogram equalization assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities.
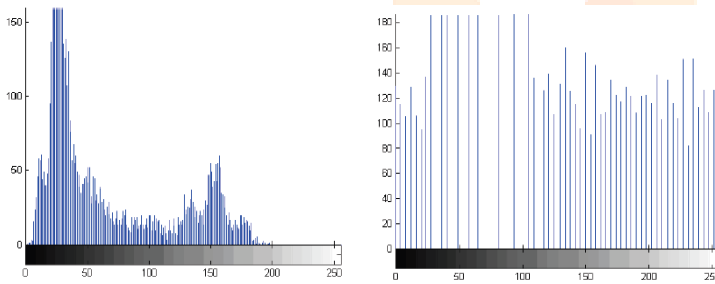
5. Edge Detection Techniques

5.1 Morphological Edge Detection

The morphological concept and technique constitute a powerful set of tools for extracting feature of interest in an image. It can be used as the basis for developing image segmentation procedures with a wide range of applications. Morphology is a broad set of image processing operations that process images based on shapes. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, you can construct a morphological operation that is sensitive to specific shapes in the input image. Consider an image G defined by:

$$G = \{g(i,j); i = 1,2 \dots M, j = 1,2 \dots N\}$$

Morphological operations apply a structuring element to an input image, creating an output image of the same size. A structuring element is a matrix consisting of only 0's and 1's that can have any arbitrary shape and size. The pixels with values of 1 define the neighborhood. A configuration for structuring element B, used in this work, is shown below

$$B = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{pmatrix}$$

The most basic morphological operations are dilation and erosion. In erosion, the value of the output pixel is the minimum value of all the pixels in the input pixel's neighborhood, while in dilation, the value of the output pixel is the maximum value of all the pixels in the input pixel's neighborhood.
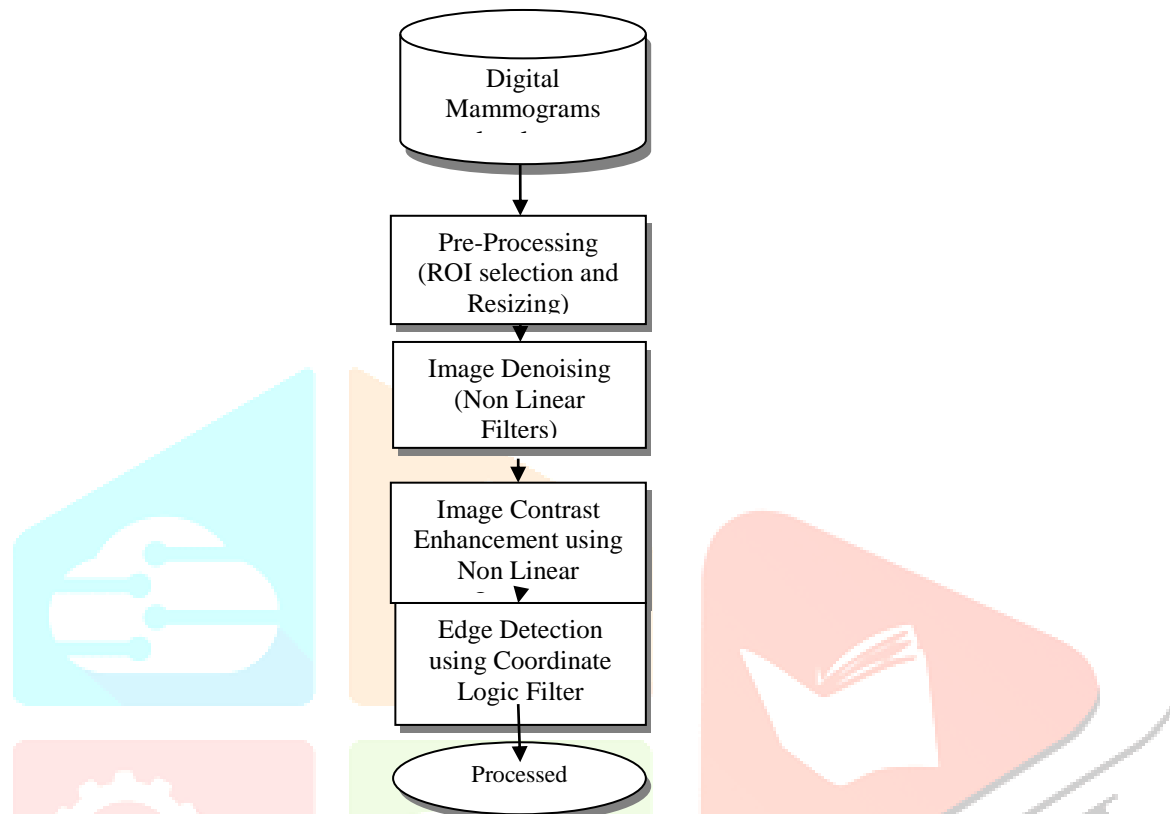
Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image.

Edge detection of MCs in a ROI image with morphological filter is achieved by:

$$F = (Gerosion) - (Gdilation)$$

Where F is the final ROI image with edge detection, G is the resulting binary ROI image. $Gerosion$ and $Gdilation$ represent the erosion and dilation of the ROI image G respectively.

Proposed Methodology And Problem Definition

Digital Mammograms

Pre-Processing (ROI selection and Resizing)

Image Denoising (Non Linear Filters)

Image Contrast Enhancement using Non Linear

Edge Detection using Coordinate Logic Filter

Processed

Block diagram representation of the approach implemented in MATLAB7.6

In this section, an overview of the proposed method for detection of MCCs in digital mammography is explained. The system described by block diagram in fig. 1 was implemented in MATLAB 7.6. In the first stage, many ROIs were selected from the mammograms and were resized; next, in the second stage we apply a Median Filter for Image Denoising of the ROI images. In the next block, we apply an Image Contrast Enhancement by applying a Nonlinear Operator. The high bright values in the ROI image are enhanced and the low bright values are diminished. Next to this, an Edge Detector involving Coordinate Logic Filters is used.

Software Requirements

This software module will be designed on MATLAB 7.6 & above versions which require following minimum system requirements for installation:-

| Operating system	Processors	External storage	RAM	Graphics
Windows XP Windows 2000 (Service Pack 3 or 4) Windows7 (Service Pack 7or 8)	Pentium III/ V/ Xeon/ Pentium M/ AMD Athlon/ Athlon XP/ Athlon MP	3.72 GB (MATLAB only with help)	256 MB (Minimum) 512 MB (Recommended) 2 GB	16-, 24-, or 32-bit OpenGL capable graphics adapter DirectX 9.0c (August 2005) or later Yet 2012 and onwords

Original Mammographic Image with MCCs
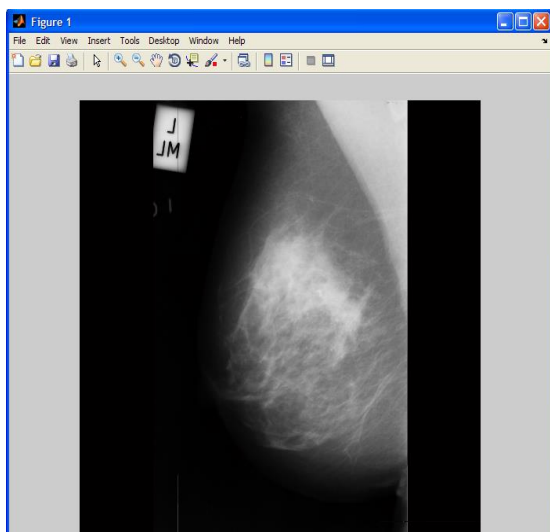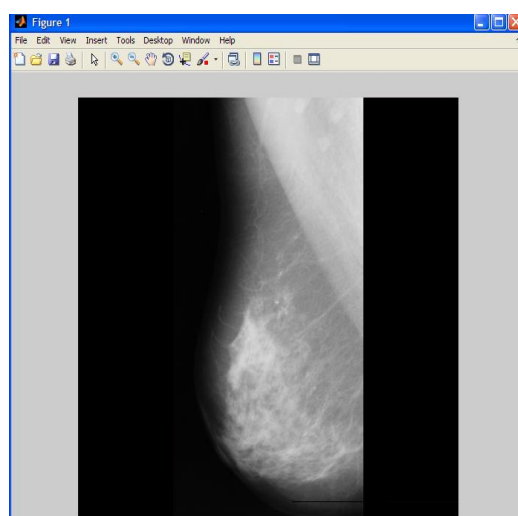

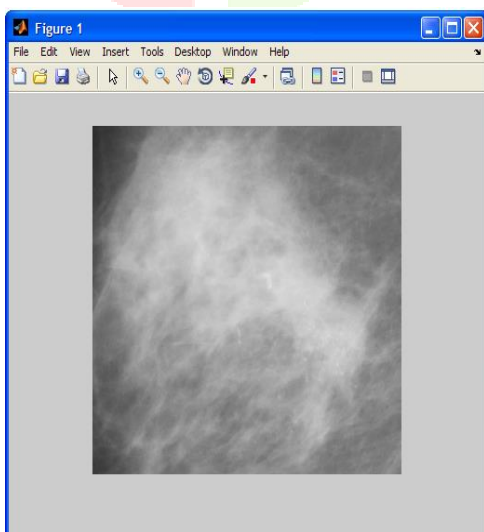(a) Original image 1
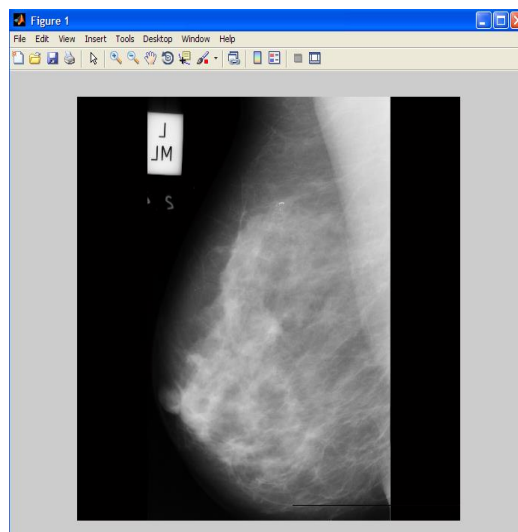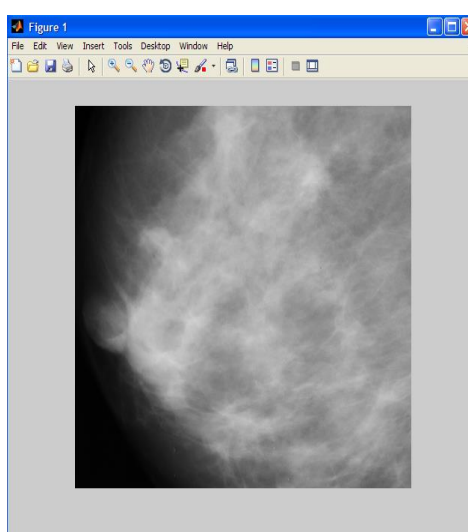

(b) Original image 2
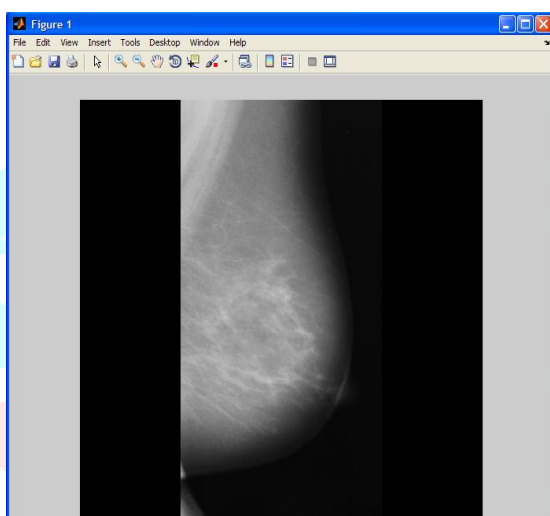
(c) Original image 3

(d) Original images 4

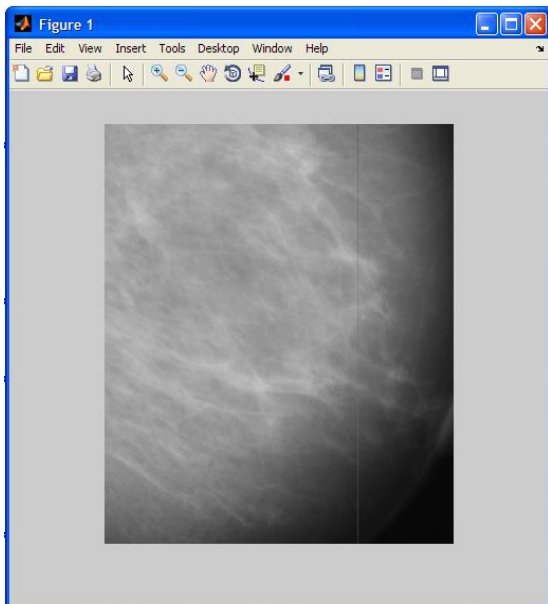**Figure (a, b, c, d): These are the original figure used for our work**

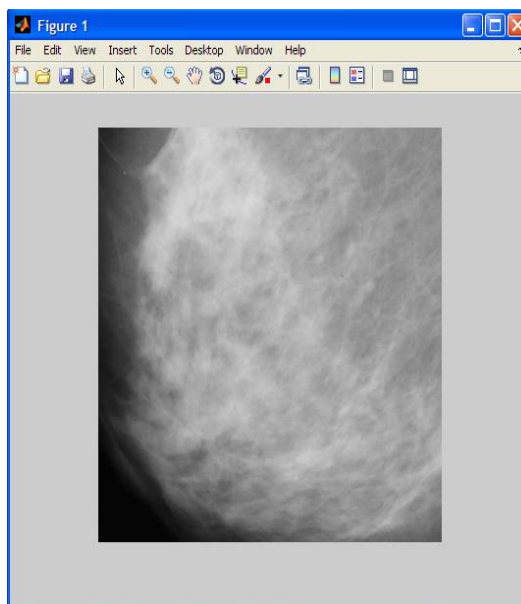**ROI selected Denoised Image after Median Filtering**

(a)Denoised ROI Image with PSNR value 53.2675
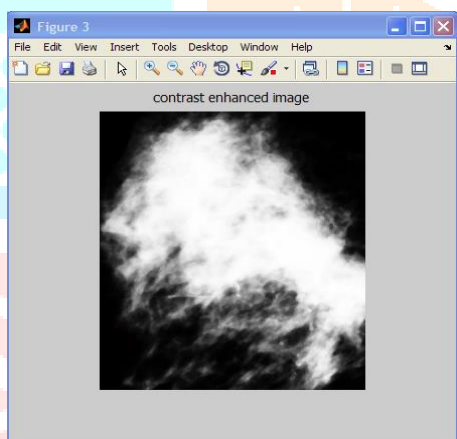

(b)Denoised ROI Image with PSNR value 55.8390

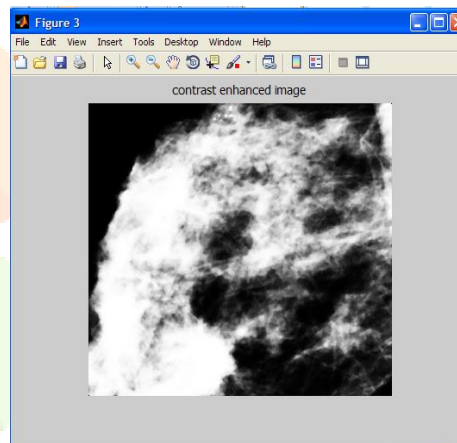(c)Denoised ROI Image with PSNR value 56.4240   (d)Denoised ROI Image with PSNR value 57.1787

Figure (a, b, c, d): Denoised Image with corresponding values of PSNR value

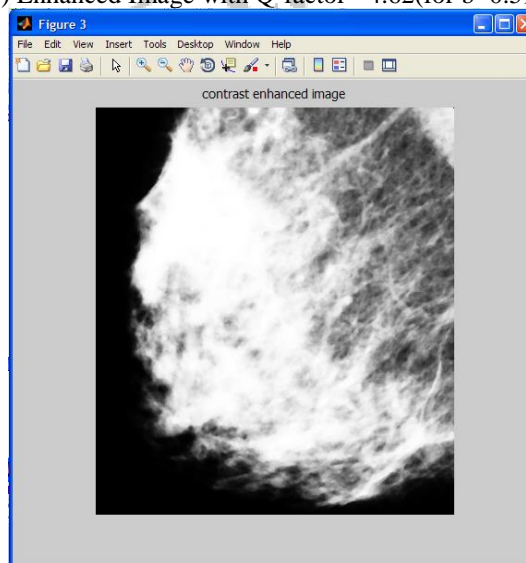**Image after Applying Contrast Enhancement Operator**

(a)Enhanced Image with Q-factor =5.35(for b=0.65, c=29)   (b) Enhanced Image with Q-factor =4.62(for b=0.59, c=50)
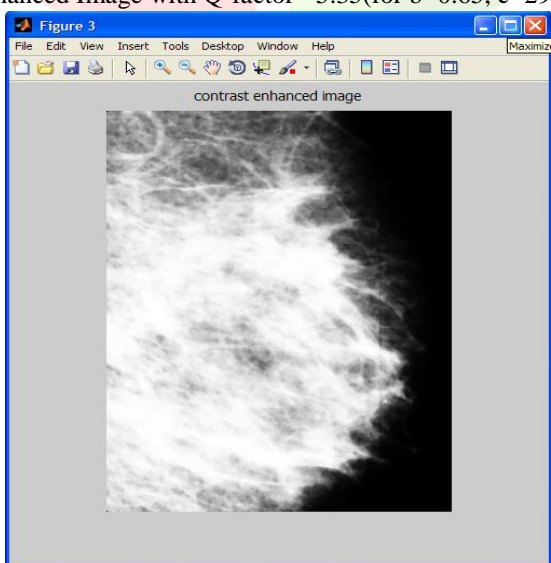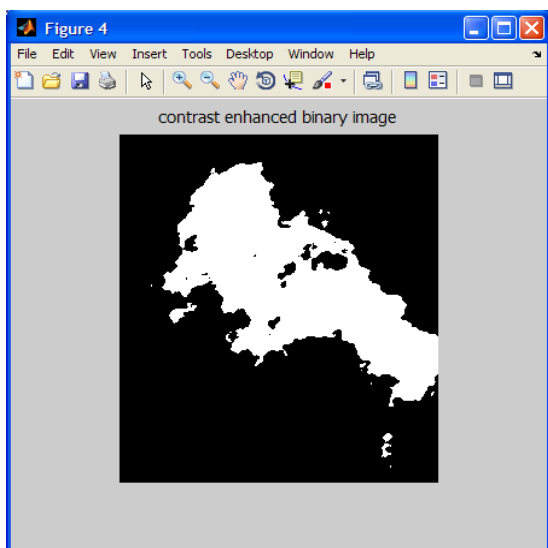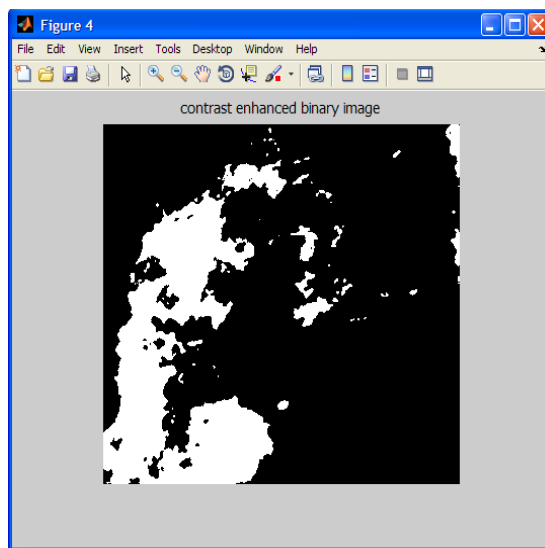

(c)Enhanced Image with Q-factor =4.86(for b=0.55, c=32)   (d) Enhanced Image with Q-factor =4.82(for b=0.57, c=27)

Figure (a, b, c, d): Enhanced Image with corresponding Q-factor values for different b and c.
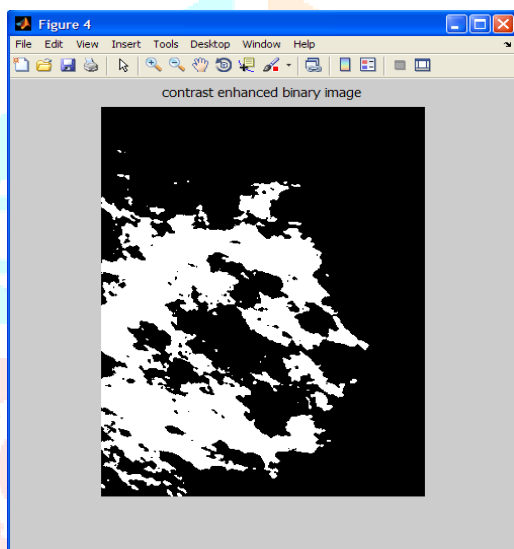
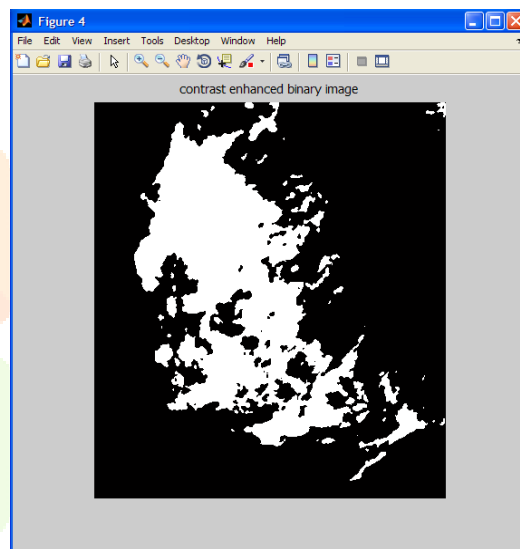**Binarization of Contrast Enhanced Image**

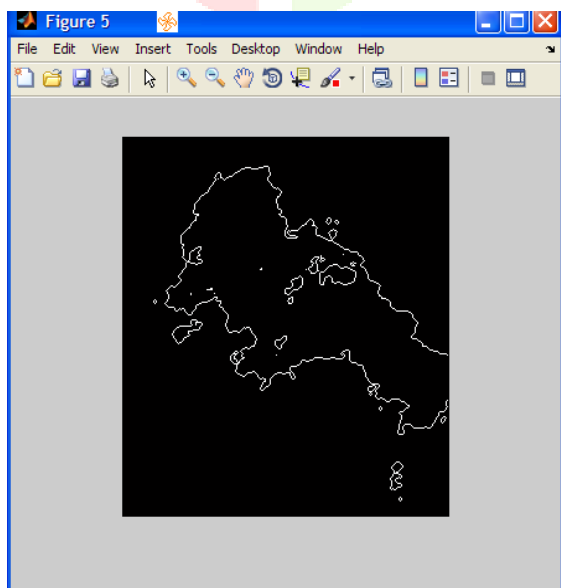(a) Binary Image 1
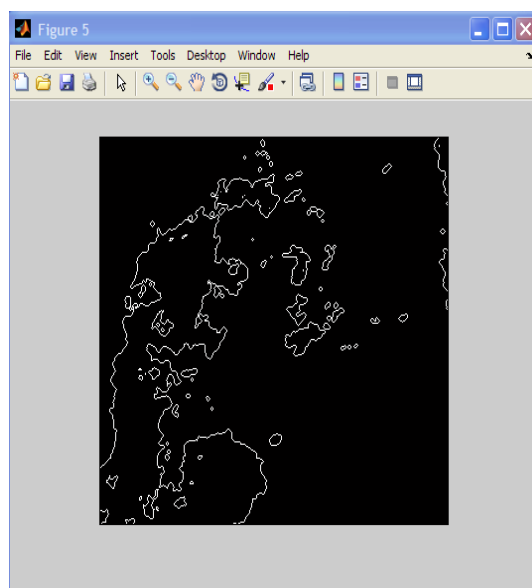

(b) Binary Image 2

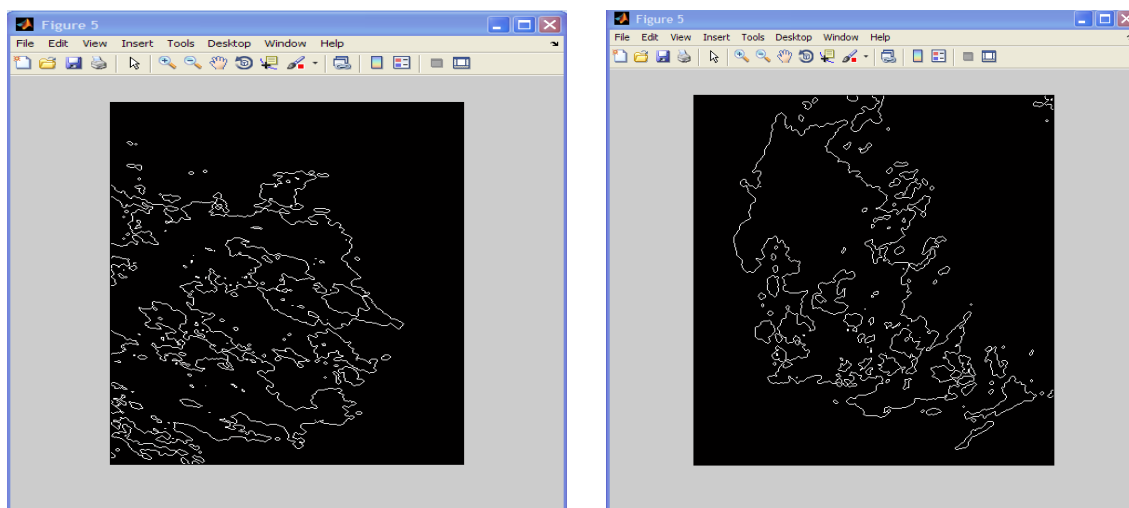
(c) Binary Image 3

(d) Binary Image 4

Figure (a, b, c, d): Corresponding Binarized Image.
Edge Detection of Image

(a)Edge detected Image with Edge Similarity index=0.0201   (b)Edge detected Image with Edge Similarity index=0.880

(c)Edge detected Image with Edge Similarity index=0.106 (d)Edge detected Image with Edge Similarity index=0.5625

Figure (a, b, c, d): Edge detected Image with corresponding Edge Similarity Index values.

Results & Discussions

ROI selected Image	PSNR value after Median Filtering(in db)	Type of tissue	Degree of abnormality	Value of b and c for Contrast Enhancement	Q-factor after Image Enhancement	Edge Similarity value after Edge Detection
ROI 1(209)	53.2698	Grandular	Malignant	c=29 , b=0.65	5.3531	0.0201
ROI 2(219)	55.8390	Grandular	Benign	c=50 , b=0.59	4.622	0.8800
ROI 3(238)	54.4240	Fatty	Malignant	c=32 , b=0.55	4.8694	0.6832
ROI 4(249)	57.1787	Dense	Malignant	c= 27, b=0.57	4.8214	0.5605

This section presents some experimental results of our proposed method. To test our method, we selected several ROIs images from mammograms with dense pattern tissue and the presence of MCCs. ROI images are selected and resized to test our method to show our results.

The second column of the table shows the results of PSNR values after denoising the image after passing through 3x3 median filter. The visibility of MCCs is improved using image enhancement by histogram adaptive equalization technique.

The next column shows the resulting ROI image with parameter control of threshold β and the rate of enhancement c. This parameter must be predetermined by hand and produce good results in image enhancement step. It is followed by the quality factor values computed after applying image enhancement operator.

The last column shows the results of MCCs edge detection by coordinate logic filter by evaluating the values of edge similarity index. Due the obtained results, the proposed method is a good alternative in order to detect MCCs, which can be compared with other works.

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