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Microcalcifications Detection Using Image And Signal Processing Techniques For Early Detection Of Breast Cancer

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MICROCALCIFICATIONS DETECTION USING IMAGE AND SIGNAL PROCESSING TECHNIQUES FOR EARLY DETECTION OF BREAST CANCER

by
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This dissertation, submitted by Md. Shafiul Islam in partial fulfillment of the requirements for the Degree of Doctor of Philosophy from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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Md. Shafiul Islam
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TABLE OF CONTENTS

LIST OF FIGURES

Figure Page

LIST OF TABLES

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To my parents

ABSTRACT

Breast cancer has transformed into a severe health problem around the world. Early diagnosis is an important factor to survive this disease. The earliest detection signs of potential breast cancer that is distinguishable by current screening techniques are the presence of microcalcifications (MCs). MCs are small crystals of calcium apatite and their normal size ranges from 0.1mm to 0.5mm single crystals to groups up to a few centimeters in diameter. They are the first indication of breast cancer in more than 40% of all breast cancer cases, making their diagnosis critical. This dissertation proposes several segmentation techniques for detecting and isolating point microcalcifications: Otsu's Method, Balanced Histogram Thresholding, Iterative Method, Maximum Entropy, Moment Preserving, and Genetic Algorithm. These methods were applied to medical images to detect microcalcifications. In this dissertation, results from the application of these techniques are presented and their efficiency for early detection of breast cancer is explained. This dissertation also explains theories and algorithms related to these techniques that can be used for breast cancer detection.

CHAPTER 1

INTRODUCTION

Breast cancer is one of the major causes of death among women throughout the world. As indicated by the American Breast Cancer Society, breast cancer malignancy is the second leading cause for mortality among women in the US [1]. In 2016, more than 246,660 women in America will be affected by breast cancer, and more than 40,450 women will die from the disease [2]. In breast cancer, cells from a small area of the breast begin developing with a sporadic growth pattern. These additional cells or the unpredictable development of cells are called cancerous cells. This can be further sorted as benign or malignant. Early detection and treatment of this disease can increase the possibilities of survival.

Breast cancer death rates, for the most part, increase with age. 95% of new cases and 97% of breast cancer deaths happen in women 40 years old and older [3]. The American Malignancy Society suggests that patients with a family history of breast cancer or who are more vulnerable against the illness because of different components be screened every year starting at age 40, or 10 years before the period of diagnosis of a first-degree relative with the disease [1]. At the point when screening highly vulnerable women, microcalcifications can be detected by mammography in 36% of the cases and they can be detected by mammography and MRI in 92.7% of the cases [4]. The rate of distinguishing breast cancer in highly vulnerable women utilizing mammography and ultrasound is 52%, contrasted with 92.7% of joined mammography and MRI [4]. In this manner, the consolidated adequacy for distinguishing breast cancer with mammography, ultrasound, and

MRI is much higher than that when using only one of these imaging methods. At the point when breast cancer is analyzed, an ultrasound or MRI guided biopsy can affirm the growth of the disease. By and large, ultrasound-guided biopsy is favored on account of its lower expense, relative simplicity, and higher level of patient solace. A few treatment choices are available after the finding of breast cancer. The most well-known treatment is breast mastectomy, which evacuates malignant tissues and keeps cancer from spreading. Indeed, even after a breast mastectomy, breast cancer may reappear and still be a reason for death [5].

Diagnosis of breast cancer in an early stage is the essential way of surviving from this disease. Breast cancer diagnosis is possible utilizing advanced X-ray, ultrasound, Magnetic resonance imaging (MRI) or breast biopsy. As of now, X-ray mammography is the most acknowledged system for identifying breast MCs. For early breast cancer identification, mammography has turned out to be very popular and the most used technique. Detection of breast cancer malignancy through mammograms and segmentation of mammogram images is the key operation that segments that afflicted part from the tissue and background. The objective is to discover the area of interest for mammograms and to find the suspicious region. The segmentation of mammograms becomes difficult because of differing densities of breast tissue structures. At the point when pixels are not effectively segmented, it results in false positive and false negative results [5].

Then again, this imaging methodology exhibits a few weaknesses and impediments. Mammography exposes patients to ionizing radiation and is generally ineffective in women with dense breasts [6]. As of late, new imaging strategies have been utilized to supplement X-ray mammography and overcome some of its constraints and drawbacks. In addition, just around 10 - 25% of mammographically suspicious lesions are observed to be harmful from tissue biopsy,

bringing about pointless and excessive biopsy procedures [7]. Ultrasound imaging, then again, is a non-ionizing strategy and hence could be a safer technique for breast MCs identification [8]. However, current cutting edge clinical ultrasound scanners cannot distinguish MCs in the size scope of clinical interest (0.1-0.5 mm). The low detection rate of MCs with ultrasounds is because of the low spatial resolution of the ultrasound images and the presence of spatial noise, which covers the small MCs. Ultrasound imaging has low image resolution and does not have adequate information which can be found in computerized X-rays. Because of this reason, ultrasound is not recommended by the U.S Food and Drug Administration (FDA) as a strategy for breast cancer diagnosis in earlier stages [7].

Calcifications are very significant findings on X-rays. Many radiologists consider calcifications 0.5 mm or less to have great possibilities of being related to cancer; and calcifications of 2.0 mm or bigger are considered non-threatening. The minimum observable calcifications on a mammogram are around 0.2 - 0.3 mm. The quantity of calcifications that make up a bunch has been utilized as a pointer of benign or malignancy. While the real number itself is discretionary, radiologists have a tendency to concur that the base number of calcifications be four, five, or six to be of importance. Any number of calcifications under four will seldom prompt the recognition of breast cancer all by itself. Once more, as with all criteria in mammographic investigation, no number is supreme and a few calcifications may justify more prominent suspicion on the off chance that they show troubling morphologies. The morphology of calcifications is thought to be the most critical marker in separating benign from harmful. Round and oval formed calcifications that are additionally uniform size will probably be on the benign end of the range. Calcifications that are unpredictable in size fall closer to the malignant, calcifications have been portrayed as little parts of broken glass and are once in a while round or smooth [7].

Up to this point, the best methodology for identifying and diagnosing breast cancer has been mammography [9]. On the other hand, there are several limitations of mammography in breast cancer detection. Numerous pointless (65–85%) biopsy operations are done because of the low specificity of mammography [6]. The superfluous biopsies build the expense, as well as make the patients experience the ill effects of emotional stress. Mammography has likewise been less successful in distinguishing breast cancer in women with dense breasts. Moreover, the ionizing radiation of mammography may be destructive for both patients and radiologists.

Ultrasound (US) imaging is an imperative distinct option for mammography. Scientists and specialists are demonstrating an expanding enthusiasm for the utilization of ultrasound images for breast cancer detection [10, 11]. Insights demonstrate that more than one out of four studies on breast cancer detection depends on ultrasound images, and the extent is quickly expanding [12]. Studies have shown that utilizing US pictures can segregate benign and malignant masses with a high precision [6, 13]. Utilization of ultrasound can increment overall cancer identification by 17% [8] and lessen the quantity of pointless biopsies by 40%, which can save up to $1 billion every year in the United States alone [14]. Breast ultrasound (BUS) imaging is better than mammography in many ways. Since it uses a non-ionizing radiation, ultrasound examination is more helpful and more secure than mammography for patients and radiologists for regular examination [15]. It is additionally less expensive and quicker than mammography. Along these lines, ultrasound is particularly suitable for use in developing countries in many continents. Ultrasound methods are more effective than mammography for identifying variations from the norm in dense breasts; hence, it is more significant for women younger than 35 years old [4]. There is a high rate of false positives in mammography, which causes a great deal of superfluous biopsies [6]. In comparison, the accuracy rate of breast ultrasound imaging for detecting cysts is much more than

mammography [7]. Hence, ultrasound imaging is one of the most significant diagnostic tools for breast cancer detection.

Still, medical ultrasound imaging techniques are able to reliably distinguish between tumors of different sizes, regardless of a significant number of millimeters in size. This is because of their low resolution, the presence of speckle noise in their images, phase aberration, and attenuation. On the other hand, Ultrasound has greater effect as a result of its low cost, minimal effort, availability and movability. Primary caution of conceivable breast cancer growth can be recognizable by late therapeutic detecting as microcalcifications advance. In less than 40% of all breast cancer, they are the first indication of the disease, and it's truly difficult to distinguish them in view of their little size. So early identification of breast cancer is imperative to keep this ailment from turning into an explanation behind death of numerous patients [5].

Because of their small size, microcalcifications detection is very critical for early detection of breast cancer. Therefore, the goal of this dissertation is to improve the quality of breast images in order to detect microcalcifications. This goal was achieved through the following objectives:

Firstly, image processing techniques for detecting and isolating point microcalcifications were investigated. Secondly, signal processing techniques to increase the image resolution for detecting point microcalcifications were investigated.

The following segmentation techniques were used for detecting and isolating point microcalcifications: Otsu's, Balanced, Iterative, Maximum Entropy, Moment Preserving, and Genetic Algorithm. These methods were applied to X-ray, MRI and ultrasound images as well as on numerical phantoms.

In this dissertation, different image segmentation techniques were used for early detection of breast cancer. Segmentation is an important development in automated investigation where structures of interest are identified and differentiated from background tissue. It is also helpful for feature extraction, image property calculation and image presentation. In this dissertation, several image segmentation techniques for microcalcification detections are presented. Signal processing techniques were used to improve the resolution of ultrasound images.

CHAPTER 2

STATE OF THE ART

X-ray Mammography is the most widely used medical imaging modality for early detection of breast cancer. X-ray Mammography uses X-ray radiation in the frequency range of 30 petahertz to 30 exahertz (3×10^{16} Hz to 3×10^{19} Hz). It produces an image that is a projection of the entire breast (3D to 2D). Its spatial resolution of the mammogram image is approximately 20 lines pairs/mm. This method can detect approximately 78% of invasive breast cancer [4] and its sensitivity is as high as 98% in women over 50 years old with fatty breasts [4]. One of the major limitations of X-ray mammography is its low sensitivity in dense breasts. Mammograms of dense breast tissue common in younger women are difficult to interpret. Dense breasts are more likely to develop breast cancer and the sensitivity of mammography in these dense breasts can be as low as 30%-48% [9]. Another disadvantage of mammography is the exposure of patients to the X-ray ionizing radiation, which may induce cancerous cells. In addition, the mammography screening process is sometimes uncomfortable because the breast has to be compressed between flat surfaces to improve image quality.

Digital mammography has shown better results for screening breast cancer for the women with dense breasts and it's more sensitive in women with dense parenchyma and premenopausal women and for those women who are under 50 [16]. However, digital mammography does not eliminate the fact that small, non-calcified breast cancers can be obscured by dense parenchyma [17]. Among almost 50,000 women who participated in the Digital Mammographic Imaging Screening Trial

(DMIST), the overall sensitivity of the screening mammography was only 55% [16]. With the errors approximately half of the cancers are visible in retrospect due to the lack of recognition of the suspicious nature of the lesion. By using double reading one can improve detection by 7% to 15% [12]. Physician experience also plays an important role for detecting breast cancer in the early stage. Due to wrong interpretations sometimes breast cancer is not detected. Despite improvements and technological modifications done regarding mammography, still now at least 10% of breast cancers remain unidentified mostly due to dense parenchyma [13]. For this reason, ultrasound imaging and magnetic resonance imaging have been used for further confirmation of breast cancer when screening a patient along with mammography. For wider excisions and even mastectomies improved identification of disease extent is necessary[18].

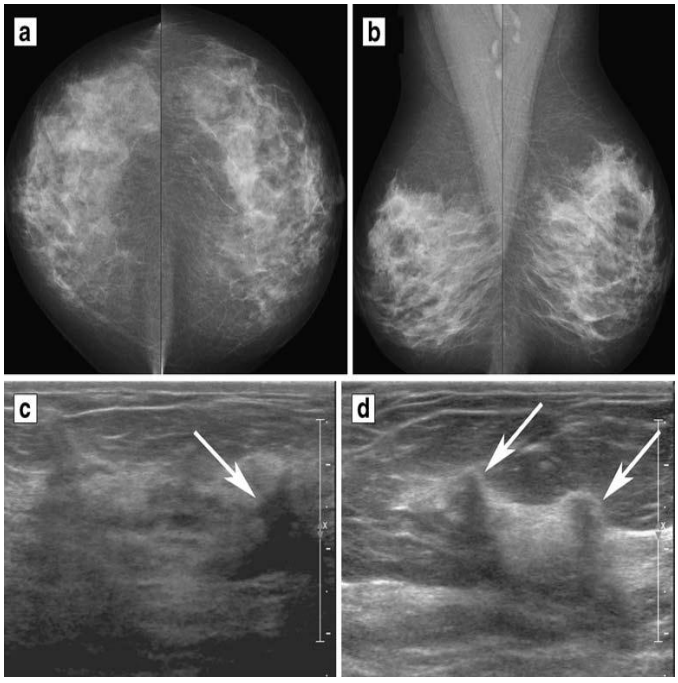

Figure 2.1: On mammogram images (a), (b) arrows shows a 7 mm (c) and 10mm (d), grade I, stage 1, invasive ductal carcinoma in situ on right and left breast respectively [9].

With ultrasound imaging, breasts are irradiated with sound waves through a probe containing an array of transducers. The frequency of sound waves is of 2- 20 MHz, which is much lower than

the frequency range of X-ray, and, thus is safer. Ultrasound imaging systems produce images of a single plane. These systems provide images in real time with a frame rate of 25 frames per second. Because of advances in transducers and ultrasound technology, current ultrasound imaging systems can detect breast cancers as small as 3 mm [4]. Recent studies suggest a predictive value of almost 98% for detecting invasive lobular carcinomas when both mammography and ultrasound imaging are used for screening [8]. In another recent study, 88% of invasive lobular carcinomas that were identified mammographically were also detected with ultrasound imaging [14]. Other studies showed that additional cancers were detected with ultrasound screening of women who had already been screened mammographically. Results of a recent study show that with an increase in breast density, the detection rate of breast cancer also increases with the use of ultrasound screening.

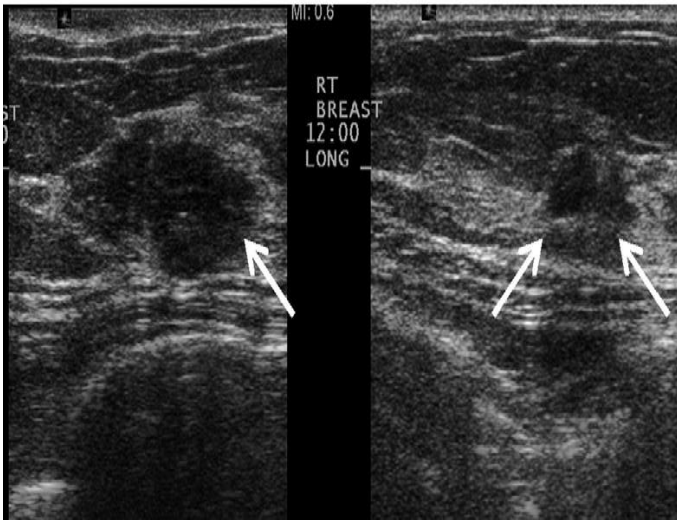

Figure 2.2: Longitudinal grayscale ultrasound images show two irregular hypoechoic masses (arrows), measuring 1.5 cm and 0.6 cm at the 10- and 12-o'clock positions respectively in the right breast. Ultrasound-guided core needle biopsies revealed intermediate grade ductal carcinoma in situ at both sites [4].

In a more recent study, women with heterogeneously dense and extremely dense parenchyma who had negative mammograms were found to have bilateral breast cancers when screened with

ultrasound. Overall, ultrasound screening of mammographically negative dense breasts contributed to an additional cancer detection rate of 20% in asymptomatic women, compared with mammography alone, while maintaining a very low surgical biopsy rate (0.9%) [15]. The contribution was substantially greater for younger women than for older ones in the proportion of cancers detected (an additional 41.3% for under 50 years relative to an additional 13.5% over 50 years) [19]. These findings suggest that routine ultrasound screening in asymptomatic women might provide the greatest relative cancer detection yield if applied to women under 50 years of age with dense breasts [4]. Although ultrasound screening is very helpful in detecting breast cancer, in some cases it has a higher false positive rate and lower specificity. In addition, ultrasound imaging is highly operator-dependent, requiring real-time adjustments of gain, focal zones, dynamic range, pressure, patient positioning, and, most importantly, recognition of abnormalities. Therefore, ultimately, if ultrasound imaging is to be used as a supplemental screening tool, the current model of physician-performed scanning using hand-held transducers will likely need to be changed [8].

Automated ultrasound imaging allows for reproducible image quality and consistency, and removes user variability [6]. However, there are limitations to using this technique because the resolution of the images obtained by most automated scanners is sometimes limited [5]. Furthermore, there is a learning curve with automated ultrasound imaging, as physicians need to gain familiarity with interpreting the data sets on a workstation. As vendors continue to improve image quality, automated breast ultrasound is likely to become a helpful tool for breast cancer screening [20]. Older technology enabled only differentiation of “cyst” versus “solid,” whereas the higher-frequency transducers available today provide greater shape and margin definition, internal characteristics, and vascular patterns of solid masses such that better differentiation of

benign and malignant is possible. Hence, further recommendations for biopsy or follow-up can be more confidently made. Ultrasound also provides the best guidance method for biopsy of suspicious lesions in terms of cost, ease, and patient comfort. Use of ultrasound imaging can determine the need for costlier stereotactic and MRI-guided procedures. As discussed previously, there are efforts being made to supplement mammography with other imaging tests in some women. Although those women at greater risk can be candidates for undergoing MRI, the majority, at low or intermediate risk, do not qualify. For these women, primarily those with dense tissue, screening with ultrasound imaging is suggested for early detection of breast cancer.

Magnetic resonance imaging (MRI) is a valuable tool for local staging before breast cancer surgery. Small invasive cancers and ductal carcinoma in situ can be detected using breast MRI due to remarkable advances in temporal resolution and spatial resolution [21]. For high-risk women, when supplemental screening is planned, MRI is performed in lieu of ultrasound imaging. The American Cancer Society has updated its breast cancer imaging guidelines and now advocates breast MRI for certain groups of high-risk women [22]. MRI uses a large magnet of 3-5 Tesla and RF coils to produce 3D images of the breast. The signals received are processed to produce the images. Compared to other imaging techniques, MRI is relatively expensive and requires an intravenous injection of gadolinium, which causes the development of nephrogenic systemic fibrosis in a small group of patients with impaired renal function [23]. Therefore, a patient with a history of renal disease may not be able to undergo breast MRI. MRI also cannot be performed for breast cancer detection in patients who have pacemakers or any metal implants [24]. MRI imaging techniques are time-consuming and produce blurred images. Misinterpreted MRI images require that patients undergo the same imaging process several times. Although MRI may save patients

from unnecessary surgery, there is a concern that findings on MRI may prompt unnecessary excess tissue removal or in some cases unnecessary mastectomy.

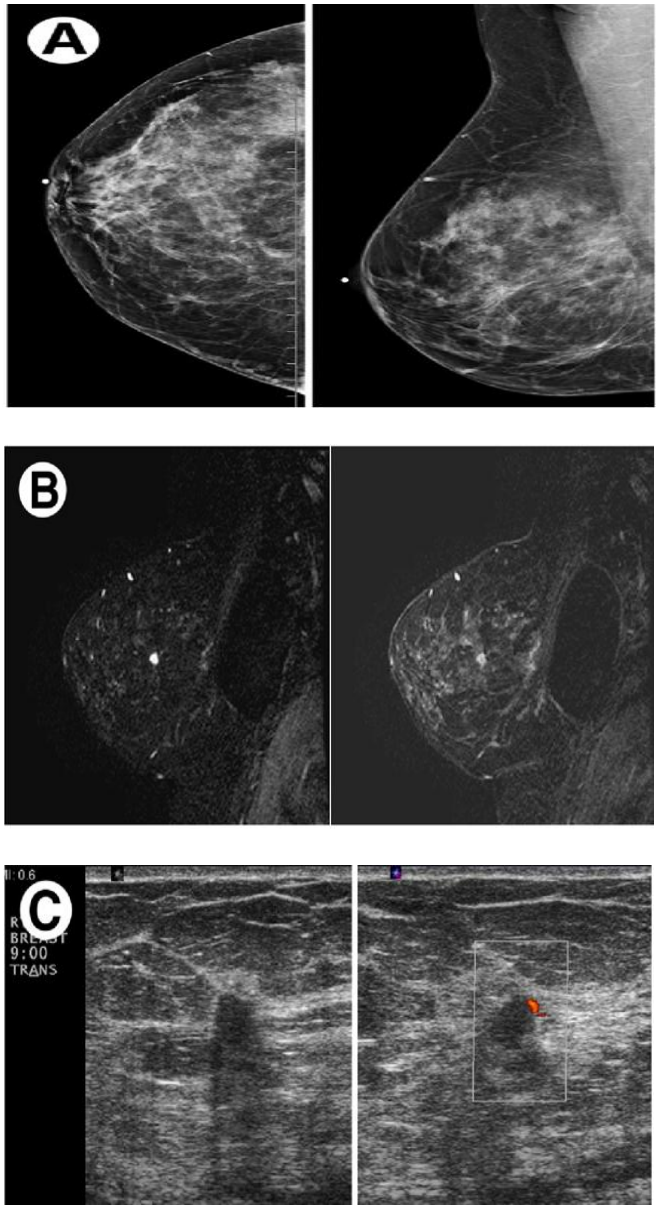

Figure 2.3: Annual mammography screening done upon a 59-year-old woman with a strong family history of breast cancer. No suspicious mammographic findings were identified. (B) Then the patient went through MRI screening on the same day and an 8-mm suspicious mass at the 9-o'clock position was found using MRI screening. (C) Later on transverse grayscale and power Doppler ultrasound images of the right breast in the 9-o'clock region show a corresponding 7-mm irregular mass with peripheral vascularity. Then Ultrasound-guided biopsy was performed, revealing evidence of invasive ductal carcinoma [4].

When lesions are identified, using MRI is a reliable method for biopsy or localization of breast cancer. Many breast biopsy systems are beginning to reach the market; however, they are hardly ubiquitous. For all the imaging techniques that have been investigated, MRI has the highest sensitivity for detecting invasive breast carcinoma and can provide valuable information that is not apparent on the mammogram. Breast MRI screening is very encouraging when applied to high risk groups [23].

Using different techniques microcalcification detection can be done and those techniques can be categorized into two main divisions: supervised and unsupervised method. Unsupervised algorithms are entirely automated and regions of interest are identified with high density, whereas supervised algorithms depend on the operator. It involves diverse algorithms such as Image-domain or region of interest based techniques (Split-merge techniques, Region growing, Neural-network techniques, Edge detection), Fuzzy techniques, feature-space based technique, clustering based (K-means, C-means, E-means), Wavelet transforms based techniques.

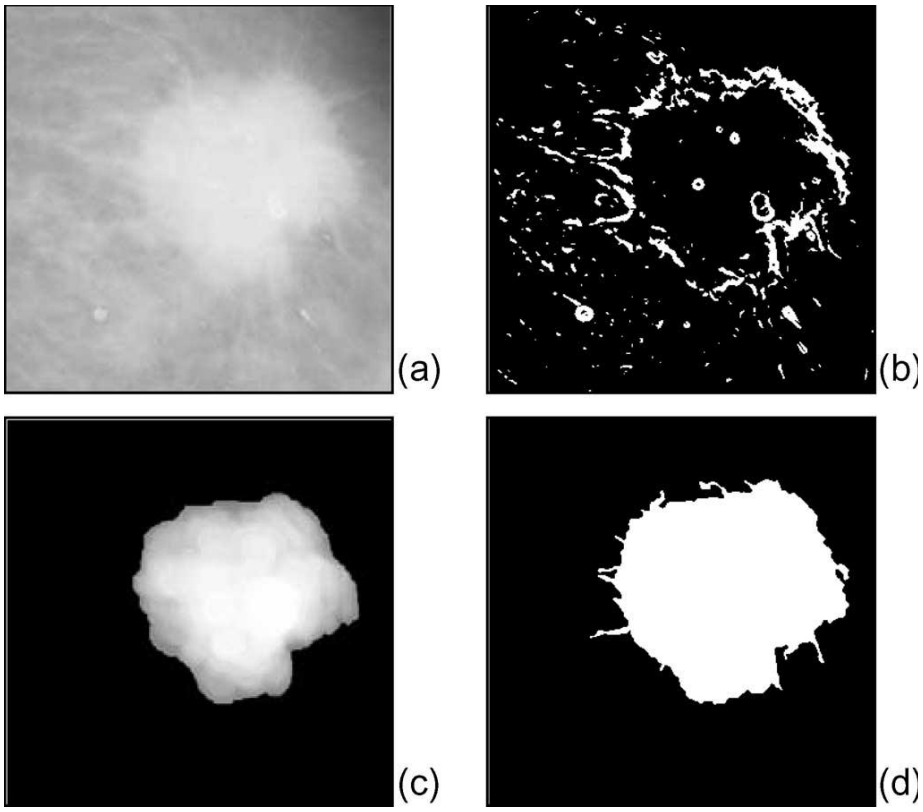

Figure 2.4: (a) Original mammogram. (b) Effect of gradient processing. (c) Image after filtering original image. (d) Final segmented mammogram image after applying wavelet transform based technique [25].

Many other algorithms such as watershed transformation, clustering and soft computing techniques i.e. using Neural Network and Fuzzy Logic, and Region Growing, and Edge Detection, and many others can be utilized for early detection of breast cancer.

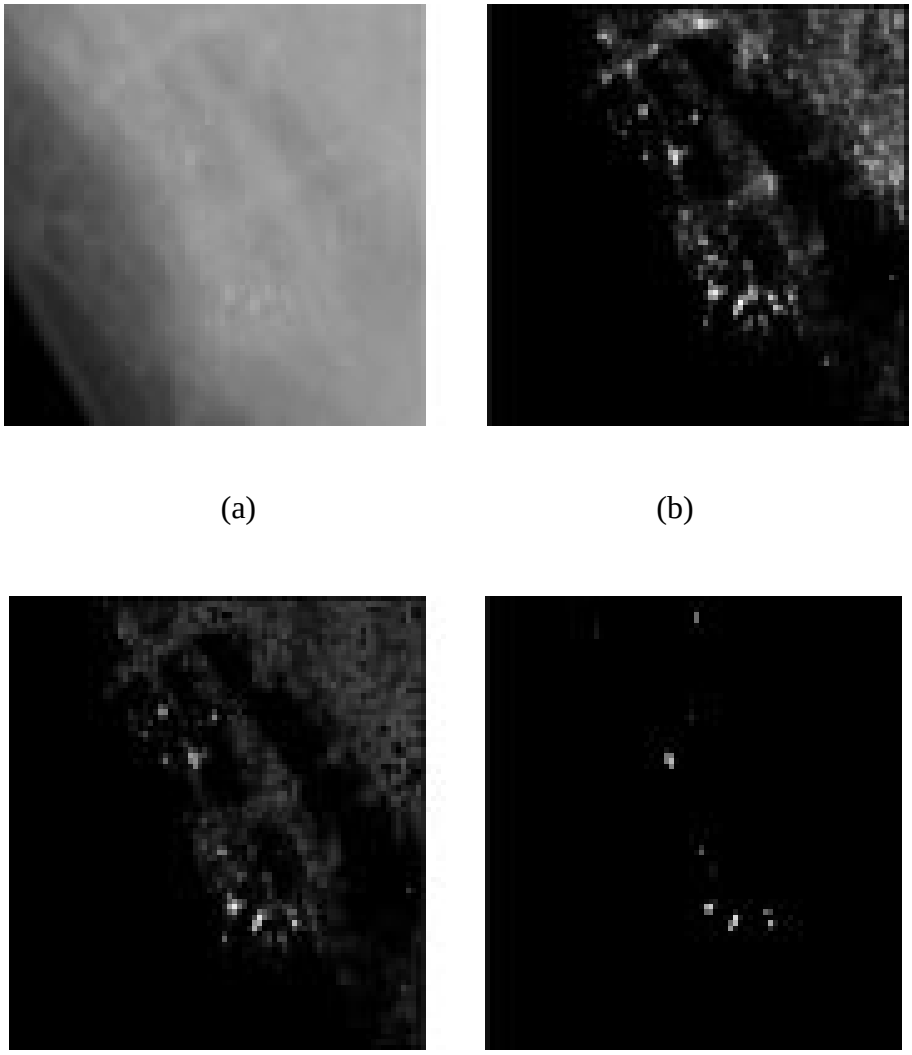

Figure 2.5: (a) The original mammogram image, (b) enhanced image, (c) enhanced image after irrelevant breast-structure removal, and (d) final resulting image after applying fuzzy logic [26].

Gabor filters can be used to process a mammogram image for microcalcifications detection [Rogova et al. Bhangale et al] [27]. By varying the center frequencies of the Gabor filter, this technique could alter the main images into different scales and coordination spaces. The filtered images are separated into small non-coinciding blocks. For every block, the mean and standard deviation of the intensities are calculated and a feature vector is formed. The method resulted in

93.48% true positive and 1.09% false positive detection rate on 32 mammogram database images [27].

Netsch and Peitgen [28] used a Laplacian of a Gaussian filter to process mammogram images for microcalcifications detection. By varying the size of the filter, this technique converts the original image into different levels of spaces. By the Laplacian matching before Gaussian response of microcalcifications with a standard value, Netsch and Peitgen [28] could determine whether a spot is a microcalcification or not. This technique was applied on 40 mammogram images and had an 84% detection rate at the price of 1 false positive per image [27].

Another microcalcification detection technique uses a different approach. The first stage of this technique is to extract an area of interest that significantly corresponds to microcalcifications by examining the distribution of brightness over the mammogram. Then identification of microcalcification clusters are determined as regions of interest. Then, the final stage requires reconstructing the data that might have been absent in the previous stages [29].

Meta-heuristic algorithms were proposed by Thangavel and Karnan [30] for microcalcifications detection. This algorithm utilizes the meta-heuristic methods such as Ant Colony Optimization (ACO) and Genetic Algorithm (GA) for identifying regions of interest of a mammogram image. This technique depends on the properties of bilateral asymmetry [30]. From this method, if the structural asymmetries between the left and the right breast are stronger, probabilities of microcalcifications are higher. Bilateral subtraction is utilized to identify the structural asymmetry. In this process, primarily the mammogram images are enhanced utilizing a median filter, the pectoral muscle region is removed, and the breast border is identified. Then the genetic algorithm is implemented to enhance the detected border area. Then image alignment is done following

border points and nipple position. After that, images are subtracted to identify the desired region of interest for microcalcifications detection. According to the authors these algorithms were implemented on 322 mammogram images to detect microcalcifications [30].

A machine learning technique called relevance vector machine (RVM) can be used for microcalcifications detection in digital mammograms [31]. This method is based on Bayesian estimation theory, of which a distinct feature is that it can return a sparse decision function that is well-defined by only a very small number of relevance vectors. In this method microcalcification detection is identified as a supervised-learning problem, and then RVM is applied as a classifier to decide at each region of interest in the mammogram if microcalcifications are present or not [31].

For the Region Growing method, normal histograms or region-growing algorithms are used for microcalcifications detection [32]. To differentiate the image into background and foreground, an intensity value is selected at the valley of the histogram. In the region-growing technique, a region of interest is developed from the starting point by summing similar adjacent pixels [33]. These techniques cannot create an appropriate boundary because of their very simplified strategy and are highly sensitive to noise. They can, however, operate as a middle step to give an irregular contour or can be added with later image segmentation procedures such as morphological operations, disk expansion, and Bayesian neural network to provide better output for microcalcifications detection.

Another algorithm called Cuckoo search algorithm, which was developed by a nature inspired method and proposed by Yang and Deb (2009, 2010) [34], can be used for microcalcifications detection. Cuckoo search algorithm is a population related stochastic global sorting out algorithm that is utilized for getting a global optimal solution for a particular problem. It was found out that

the excellence or fitness of a solution of a problem can easily be related to the estimation of the objective function. Except for extensive search, this algorithm is efficient in getting the result in more complex problems. Hence, this algorithm can be used for non-linear problems and multi-level optimizations. Trial results demonstrate that this technique enhances the perceptive ability of microcalcifications detection [34].

Model-based methods have robust noise-resilient capability and are comparatively steady for ultrasound [35]. Often utilized models consist of level set, active contours, Markov random fields (MRF) [36]. Sarti et al. [37] conferred a level set maximum probability technique to gain a maximum probability segmentation of an image. The Rayleigh probability distribution function was used to model gray level performance of sonography. The main purpose of this image segmentation is to segment an image to its minimum energy. Madabhushi and Metaxas [38] added intensity, texture information, and experimental domain information utilized by radiologists with a dynamic contour model in an effort to bound the outcomes of shadowing and false positives. Training is needed for implementing this method. Utilizing manual description of the quantity by a radiologist as a guide, and the Hausdorff space and normal space as boundary error metrics, they noted that their technique is not dependent on the number of training samples, can give better output results compared to parameters, and can provide a true positive area of 74.7%. Dynamic contour models have been implemented to 3-D ultrasound segmentation, such as [39]. Boukerroui et al. [40] utilized a Markov casual field to design the area of interest and to focus on the adaptive properties of the algorithm. This design implements a function to manipulate the adaptive feature of the segmentation procedure, and considers both local and global statistics through the whole segmentation procedure. Designers of this method are able to give strong manipulation of the pixel

correlations. Output of this segmentation result can be further enhanced using a segmentation approximation structure considering the Bayesian paradigm [41].

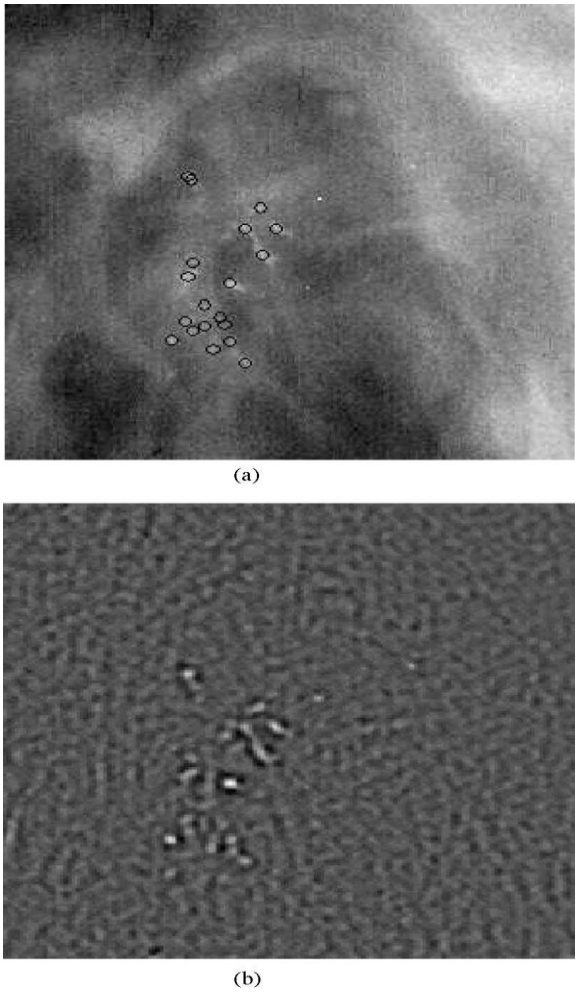

Figure 2.6: (a) Mammographic region of interest, where microcalcifications are marked with circles. (b) Output after applying support vector machine [18].

Machine learning techniques, like neural network and support vector machines [42] are well known in image segmentation. In [43], Dokur and Ölmez showed a neural network technique that shows segmented output results. Images were distributed into square blocks, and characteristics were analyzed from each block using the discrete cosine transform (DCT) process. Then a neural network was designed of three layers to separate the blocks into two categories, background and

foreground. This method can be applied on regions of interest that need to be segmented by operators. Kotropoulos and Pitas [42] implemented the support vector machine method with an outward source function kernel to categorize changed patterns and their several good output results showed that the support vector machine method could generate considerable segmented results for microcalcifications detection [18].

Using machine learning techniques, selection of characteristics and training could be two major factors that participate in a significant role on segmentation results. If these characteristics are distinct and the technique is well implemented, machine learning techniques can produce reasonable outcomes. However, excess-training or improper training procedures can significantly upset the segmentation results on new data, and to complete the whole segmentation process to detect point microcalcifications is time consuming [39].

Using signal and image processing we can detect microcalcifications more precisely in earlier stages. For signal processing, some techniques have become very popular, such as Time Reversal Multiple Signal Classification (TR-MUSIC), Artificial Neural Networks (ANN), Linear Discriminate Analysis (LDA), support vector machine method, and fuzzy logic. These computer-aided systems use great quantities of data to build models. Computer-aided detection or diagnosis (CAD) systems can take part in finding a solution for primary detection of breast cancer and can decrease the casualty rate among women with breast cancer. Normally computer-aided diagnosis can be performed in a couple of stages: preprocessing, segmentation, selection and feature extraction. Digital breast tomosynthesis mammography (DBT) is another method being built up to get better detection and characterization of breast microcalcifications particularly in women with non-fatty breasts. In this method, multiple protuberance images are recreated by permitting illustrated assessment of lean breast segments presenting the possibility to reveal cancers

concealed by typical tissue situated on top of and underneath the lesion. Usual full-field digital mammography (FFDM) has become better by improving the ability to diagnose breast cancer for particular breast cancer patients compared to screen film mammography (SFM). Numerous works have been published mentioning difficulties regarding microcalcifications detection in early stages of breast cancer diagnosis. Tsallis entropy (TE) based method has become more popular, which also has generated a lot of important results. It is confirmed that TE provides improved thresholding results compared with the other conventionally used methods, and suggests that TE is one of the best methods for detecting microcalcifications in mammograms [44]. The fuzzy entropy principle can be used for enhancing mammograms. Fuzzification requires conversion of the assessments of the strength to a period between 0 and 1. Proper implementation of this method can be used for detection of microcalcifications for early detection of breast cancer [44].

To get a good ultrasound image there are some things that need to be done, such as speckle noise removal which generally shows the noise of the image and a lot of algorithms have been developed to reduce noise in order to measure tissue dislocation and optimize image registration. For image characteristics active contour process, Rayleigh distribution can be used to set a segmentation algorithm. One renowned algorithm for processing is the level SE algorithm based on gradient. For the analysis process of the better quality images, intensity gradient data can be used. Phases are accountable to attain the organization in an image and can be calculated over spatial scales. B-mode ultrasound segmentation can be used for comparison calculations which can give the displacement measurement of a constant. The related data of an image configuration can be utilized for the calculation of an average intensity. Edge flow method is used for boundary detection and needed for very small parameter adjustment. These edges can be found at the local maxima by the gradient operative in the strength characteristics. It can determine a flow direction at each pixel

location where two opposite direction of edge flow has happened. It has been utilized in the analytical coding design to select and add the route of modification in some characteristics such as color, texture, and phase discontinuities [41].

CHAPTER 3

METHODOLOGY

Image segmentation plays an important role for image processing. It promotes the better quality of the output result for image analysis. Image segmentation is a procedure of isolating an image into distinctive locales. One of the popular sorts of segmentation is thresholding, which endeavors to order image pixels into one of the two classes, foreground and background. Toward the end of such thresholding, every object of the image, corresponding to an arrangement of pixels, is confined from whatever is left of the regions. For this situation, the point is to locate a thresholding point. Thresholding is used to dig out an object from its background by conveying an intensity value T (threshold) for each pixel such that each pixel represents a classified object point or a background point. Each pixel location is denoted by the function f(x,y). In general T is a function of f(x,y) and for global thresholding T is a function of both f(x,y) and local properties p(x,y). In local thresholding T depends on the coordinates of (x,y) for dynamic/adaptive thresholding. One procedure is to select a grayscale value as the threshold and then categorize every grayscale by making sure whether it is positioned over or below the threshold value [45].

Images were analyzed by using the steps below. All algorithms were developed and implemented in MATLAB. For the image processing the following steps are done:

1. Read the image.

2. All the images were converted into 8-bit and 480×480 pixel format before analysis.

3. Image enhancement was performed for those images which had good image resolution using a developed image enhancement algorithm.

4. Otsu's method, Iterative, Entropy based method and Genetic algorithms were applied on all images before analysis.

5. Image analysis and extraction revealed high and low detection rates for microcalcifications.

To detect microcalcifications segmentation plays a very important role by reducing speckle and decreasing the false detection rate of the image. Thresholding can be classified into several groups for breast microcalcifications detection:

- Otsu's method
- Iterative method
- Maximum Entropy based method
- Moment Preserving
- Balanced histogram thresholding
- Genetic Algorithm

3.1 Otsu's method

Otsu's method is one of the main methods that can be used for breast microcalcifications detection. Using peaks, valleys and curvature this method does thresholding [46]. Optimum threshold level can be achieved by reducing the weighted sum inside the class variance of the foreground and background image [47]. The mean value of the background and foreground images are m_b and m_f. Variance values for background image are σ^2_b and σ^2_f for thresholding level T. Here the cumulative probability function P (T) can be defined as,

$$P(T) = \sum_{i=0}^{T} p(i)$$

Cumulative sum $p(i)$ for different classes define the threshold values. Otsu recommended reducing the weighted total of inside-class variances of the center and locale pixels to set up a most

favorable threshold [48]. This technique gives a suitable threshold value when the quantity of pixels in every class are closer to each other. The optimum threshold is described as

$$T_{opt} = \arg\max\{pf(T).Pb(T)[mf(T) - mb(T)]^2\}$$

where $pf(T)$ and $Pb(T)$ are the center and locale area probabilities, correspondingly. $mf(T)$ and $mb(T)$ are the average intensities of the center and locale areas, correspondingly [45].

In Otsu's technique the threshold level that reduces the intra-class variance can be described as a weighted sum of variances of two different sections:

$$\sigma_\omega^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t)$$

Weights ω_i are the probabilities of the two sections divided by a threshold t and σ_i^2 are variances of these sections. In this method reducing the intra-class variance is similar to the increasing inter-class variance:

$$\sigma_b^2(t) = \sigma^2 - \sigma_\omega^2(t) = \omega_1(t)\omega_2(t)[\mu_1(t) - \mu_2(t)]^2$$

which can be presented as class probabilities of ω_i and class means μ_i.

The class probability $\omega_1(t)$ is computed from the histogram at t:

$$\omega_1(t) = \sum_0^t p(i)$$

where the class mean is $\mu_1(t)$:

$$\mu_1(t) = \left[\sum_0^t p(i)\, x(i)\right] / \omega_1$$

here $x(i)$ is the assessment at the middle of the i[th] histogram bin. The class probabilities and class means can be computed iteratively [49]. This idea yields an effective algorithm. Otsu's technique generates a threshold level on scale level of 0:1 and it can be implemented in the active range of pixel probability present in the image. For example, if the image has pixel ranges from 155 to 255, in Otsu's threshold technique the threshold can be 191 if that ranges in normal regular technique and full ranges from 0-255. Algorithm for Otsu's method:

1. Calculate the intensity level of histogram and probabilities.
2. Set up initial value
3. Set possible threshold level considering maximum intensity
4. Calculate two maxima intensity level of threshold
5. Decide threshold level

3.2 Iterative method

The background and foreground are clustered into two parts in the gray level samples in this method. In this method iteration is based on the Gaussian mixture model. The average of the background and foreground image class after each iteration creates a new threshold level. The iteration process stops when the final value is sufficiently small. The ultimate best threshold level is represented by,

$$Topt = \lim_{n\to\infty}\left(\frac{mf(Tn) + mb(Tn)}{2}\right)$$

The mean intensities of the background and foreground image are mf and mb. Those are measured as the segmentation threshold of the sub-image.

Only threshold level cannot regard as real condition for image segmentation, when there is great deal sum of blurry, illuminating irregularly or locale pixel varying will affect the segmentation. However, if there is a suitable threshold level available for an image and it can separate that image into several blocks, and from those separate blocks a particular threshold level can be utilized for segmentation. However, this way toward finding a threshold level is not easy but it has high-quality results on images for segmentation, which isn't simply segmented by universal thresholding. Each pixel has a nearby pixel which is centered and discover the upper limit and lower limit in their nearby pixels [45] to find the appropriate threshold level.

The algorithm for iterative method can be written as:

1. Read input image
2. Set up optimal threshold value
3. Calculate $m_f(Tn)$ & $m_b(Tn)$
4. Calculate T_{opt}
5. Stop

3.3 Maximum Entropy based method

A better segmentation assessment should increase the uniformity of pixels inside each region of interest, and decrease the uniformity of other regions. The entropy based method is an assessment of the disarray inside a particular area of interest, which is a normal attribute to include into a

segmentation method. Entropy works as same as to the phrase related to the squared color inaccuracy that is used to measure the uniformity inside a region of interest. When each region of interest has very similar luminance, same as with the squared color, and when every pixel inside a region of interest has the same value, then the entropy of that region of interest is zero [50].

If a region of interest is over segmented, then the entropy threshold level of that region will be very small. We will be required to join the desired area entropy through an additional period or part that segmentations having some huge desired areas because at hand would instead of be a well-built bias to over-segment an image. One advance would be to employ related ideas to the previous work and multiply the anticipated region entropy segmentations with a huge numbers of areas of interest. Though the supposed region of interest entropy gives an approximation of the mean disarray within a region of interest of a segmented image, total encoding of the data of an image not only needs to encode the feature value of a pixel within the region of interest (i.e. the region entropy), but also encode a representation for the segmentation. To encode the segmented image itself, pixels need to be put in the region of interest. While the desired region of interest entropy normally decreases with the number of regions, but as desired the number of bits for a particular region of interest of a region for each pixel, a determinant we call the entropy, to maximize with the number of regions. Therefore, these two reasons can be used to counteract the results of over-segmenting or under-segmenting when evaluating a particular segmented area [50].

Entropy-based methods utilize the entropy of the center and the surroundings and the cross-entropy of the original and the binarized images. In the entropy based method the image is said to have reached threshold when the sum of the background and foreground image class also reaches its maximum and they are also considered as two different image sources. Image foreground and

background are considered as two different signal sources, so that when the sum of the two class entropies reaches its maximum, the image is said to be at optimal threshold [45].

This can be written as:

$$Topt = \arg\max[Hf(T) + Hb(T)]$$

where

$$Hf(T) = -\sum_{g=0}^{T} \frac{p(g)}{p(T)} log \frac{p(g)}{p(T)}$$

and $$Hb(T) = -\sum_{g=T+1}^{G} \frac{p(g)}{(1-P(T))} \log \frac{p(g)}{(1-P(T))}$$

The purpose of characteristic-based methods is for comparison between the gray-level and binary based images, for instance fuzzy nature resemblance and edge concurrence. A model of similar technique is moment preserving where the gray-level image preserves the information of the original binary image [45].

$$Topt = \arg equal[m1 = b1(T), m2 = b2(T), m3 = b3(T)]$$

where $$Mk = \sum_{g=0}^{G} p(g) gk$$

and $$Bk = PfMfk + PbmbK$$

The algorithm for Entropy based method can be written as:

1. Read input image
2. Set up optimal threshold value
3. Calculate $H_f(T)$ & $H_b(T)$

4. Calculate T_{opt}
5. Stop

3.4 Moment Preserving

The comparison between different thresholding techniques is described in many different sources [51]. Moment preserving is one of the most popular thresholding techniques used by Tsai [52] and these techniques gives a very good outcome for segmentation. Tsai determined the threshold level by implementing moment preserving theory and this threshold level makes sure of the perpetuation of moments of gray level allocation of a particular image when the thresholding process is done. Tsai considered that if the specific image is blurry compared to the main bi-level image where every pixel has either p1 or p2 grey level values where p1< p2 then if the moment-preserving methodology applied to it can determine a threshold level in such a way that if the gray level is below the threshold and substituted by p1 and the other gray level values that are above the threshold are substituted by p2, then the moments of that specific image will be maintained. Tsai [52] observed thresholding as a moment-preserving image alteration which improves the original image. The threshold level is selected using a technique so that the moments of a particular image are preserved as in the original image. The allocation of gray levels inside a mammogram image normally is not Gaussian and can be represented with a Gamma distribution in a superior technique since the Gamma distribution is more universally used than Gaussian and can replicate similarity and non-similarity. For this purpose, the Gamma distribution is superior to the Gaussian distribution for setting thresholding to complete segmentation of images. Gamma distribution provides us more flexibility and precision for demonstration of a gray level image [53].

To compute the optimal threshold *t* using the moment preserving method we can consider two classes. Where $\mu^k_1$and μ^k_2 are the average of two classes by n^{th} order moment of the two classes can be written as:

$$b^k\ (t) = P_1.\mu_1^k + P_2.\mu_2^k$$

Here, prior probabilities are P_1andP_2. $\mu_1$and μ_2 can also be considered as gray level values of the foreground and background pixels. From the moment preserving principle we can write,

$$\frac{d}{dt}\ b^k\ (t) = 0$$

From above equations we can write:

$$\frac{d}{dt}\ P_1\mu_1^k + \frac{d}{dt}\ P_2\mu_2^k = 0$$

We can find the derivative of average $\mu_1$and μ_2 as:

$$\frac{d}{dt}\ {\mu_1}^{\mathrm{k}} = \frac{\mathrm{k\,h(t)}}{2\ (\mathrm{m_0 a})^2}\ {\mu_1}^{\mathrm{k-1}}(\frac{\mathrm{t^2 q^2}}{\mu_1} -\ \mu_1)$$

and

$$\frac{d}{dt}\ {\mu_2}^{\mathrm{k}} = \frac{\mathrm{k\,h(t)}}{2\ (\mathrm{m_0 b})^2}\ {\mu_2}^{\mathrm{k-1}}(\mu_2 - \frac{\mathrm{t^2 q^2}}{\mu_2})$$

Solving the above equations for *t* to find the optimal threshold level we get:

$$t = (\frac{(p-k)({\mu_2}^{\mathrm{k}} -\ {\mu_1}^{\mathrm{k}})}{\mathrm{kq^2}({\mu_1}^{\mathrm{k-2}} -\ {\mu_2}^{\mathrm{k-2}})})^{1/2}$$

Where $\mu_1$and μ_2 are functions of t. The primary value of t is considered as the average gray level value and is calculated iteratively. This process continues until:

$$|t_{old} - t_{new}| < \epsilon$$

The process continues until it's less than the thresholded value ϵ. The algorithm for the moment preserving method can be written as:

1. Read input image
2. Set up optimal threshold value
3. Set up histogram
4. Initialize gray level value t_{old}
5. Calculate t_{new}
6. Repeat until $|t_{old} - t_{new}| < \epsilon$
7. Stop

3.5 Balanced Histogram Thresholding

The Balanced Histogram Thresholding method is normally used for automatic thresholding in image processing. Utilizing this method, we can isolate an image into many desired areas or objects. Segmentation of a significant image is a troublesome task in image processing and its precision level can be decided by the inevitable achievement or disappointment of image analysis and calculations of the segmentations depending on the two essential properties of intensity values, intermittence and comparability. Another way is to segment an image into areas that are comparable as indicated by a predefined criterion. Histogram thresholding methodology falls under this classification. Histograms are built by partitioning the information into equal-sized bins (called classes). At that point for all data sets, the quantity of information that falls into every bin

are counted. Frequency is presented in the vertical axis and response variable is placed in the horizontal axis. The horizontal axis consists of pixels of the image histogram and assuming that the grey level histogram represents an image, f(x,y), created of shady objects in the light background, in a manner that objects and background pixels have dark levels gathered into two prevailing modes. One evident approach to extricate the objects from the background is to choose a limit *T* that isolates these modes [54].

In balanced histogram thresholding this technique considers an image that can be separated in two main classes, and those are background, and foreground of a particular image. By finding an optimum image thresholding level this image processing technique separates the histogram into two different classes. In this technique the histogram is weighted, later tested for which side of the histogram weighs more, and then by eliminating the extra weight from that side until it gets lighter compared to other side of the histogram. Then it continues that process using the same procedure until the edges of the weighting scale meet at a balanced point which can be set as threshold. For its ease, this system is a decent decision as a first approach while showing the subject of an image thresholding automatically.

When two foremost modes differentiate the image histogram, then it is defined as a bimodal histogram. When using one threshold the whole image can be partitioned into two different sections. For example, when an image is composed of two different kinds of objects on a shady background, three or more foremost modes differentiate the whole image histogram [45]. In such a situation the image histogram needs to be divided into multiple thresholds. Multilevel thresholding can divide a particular point (x,y) related to a particular object class if T1 < f(x,y) <= T2 and to the other object class if f(x,y) > T2 and to the background if f(x,y) <= T1. Then any point (x,y) for which f(x,y) > T is called an object point, and if f(x,y) point of the histogram weighs

more, then removing the extra weight from that side of the histogram, a balanced threshold point is reached. The Algorithm for balanced thresholding can be written as follows:

1. Select an initial estimate for the threshold
2. Compare both sides of the histogram
3. Remove extra weight from either side of the histogram
4. Repeat step 2 and 3 to reach a balanced point of the histogram
5. Set that balanced point as the threshold level for image segmentation
6. Repeat steps 1 to 5

3.6 Genetic Algorithm

In this method the solution of a particular problem is simulated using evolution, beginning from a primary set of solutions or assumptions, and by creating consecutive solutions of that problem [55]. This method is normally considered as a function optimizer, and in different scientific areas this method has very good results. The application of a genetic algorithm starts with a population of chromosomes. After estimating these structures and assigning a reproductive system in a way so that chromosomes that can give a better solution of a problem will be given opportunities to 'reproduce' more than those chromosomes that are not able to give a better solution. A better solution of a particular problem is measured by comparison with the present population [56].

To build the procedure of natural choice using a computer, first we have to create an image of an element at every point during the whole process to create a generation of elements. Every element inside the data structure can show the genetic structure of a possible solution or assumption. Usually similar to a chromosome, the genetic structure of every element can be explained using fixed and certain structures. The binary structure 0 and 1 is normally used for a genetic algorithm.

This can be used as solutions of problems which we are trying to solve using Genetic Algorithm [57].

One example can be when a traveler is searching for an optimal path to travel around 10 cities. He can start from any city he wants and the solution of this kind of problem can be any ordering of the 10 cities. For example: 1-4-2-3-6-7-9-8-5-10.

A Genetic algorithm is mainly based on a reduction of a genetic procedure of usual assortment from side to side operations, for instance genetic material, inhabitant's amount, fractious pace, mutation rate and highest production. Processed images after using The Genetic Algorithm can be used for a final pathway to get better results [58].

$$\text{Fitness (x)} = \text{Numf.Numb. (Mf-Mb)}^2$$

where Numf and Numb are center and locale pixels of an image. Mf stands for strength of center pixels

$$Mf = \frac{If}{Numf}$$

where *If* is the addition intensities of center pixels of an image. Mb stands for strength of locale pixels.

$$Mb = \frac{Ib}{Numb},$$

where *Ib* is summation of intensities locale pixels of an image. Threshold is determined by the following equation:

$$\text{Fitness(x)} = \max \{\text{Fitness(x)}\}$$

where x represents threshold level. Using those imaging techniques by changing the contrast of image and processing the foreground and background image we can detect microcalcifications more effectively [45]. This assessment is gained by subtracting the strength levels of the segmented image. Further constraints are also utilized, including the peak pixel strength of the associated image, the entropy, and the combined entropy.

$$\mu = \frac{1}{N}\sum_{j=1}^{N} Pj$$

$$\sigma^2 = \frac{1}{N}\sum_{j=1}^{N} (Pj - \mu)^2$$

$$\text{Skewness} = \frac{1}{N}\sum_{j=1}^{N} \left(\frac{Pj-\mu}{\sigma}\right)^3$$

$$\text{Kurtosis} = \frac{1}{N}\sum_{j=1}^{N} \left(\frac{Pj-\mu}{\sigma}\right)4$$

$$\text{Entropy} = -\sum_{j=1}^{N} pjlogpj$$

$$\text{Joint Entropy} = \sum_{i=1}^{Nx}\sum_{j=1}^{Ny} Pijlog(Pij)$$

where *Pj* is probability density of the jth bin in the histogram and N is the total number of bins.

In the Genetic Algorithm binary coded strings are normally used. The size of the string is normally established with respect to the desired solution precision. It also uses objective function information without any gradient information. The transition scheme of the genetic algorithm is probabilistic, whereas traditional methods use gradient information [55]. Because of these features of the Genetic Algorithm, they are used as a general purpose optimization algorithm. They also provide means to search an irregular space and hence are applied to a variety of function

optimization, parameter estimation and machine learning applications [59]. Objective function and fitness function, and application of genetic operators are needed to get the threshold level.

The steps of Genetic Algorithm are shown below. The most important steps involved are the creation of solutions, defining the objective function and fitness function and the application of genetic operators. They are described in detail in the following subsection. Algorithm for Genetic Algorithm is stated:

1. Start
2. Arbitrarily initialize population
3. Calculate objective function
4. Calculate fitness function
5. Apply genetic operators to get desired solution
6. Reproduction is done inside gathered solutions
7. Crossover is done inside gathered solutions
8. Mutation is done inside gathered solutions
9. Repeat steps 1 to 5
10. Stop

A significant feature of the Genetic Algorithm is to do coding of variables that are initialized inside a problem. The most common coding technique is to convert the variables into binary strings or vectors; this algorithm works best when the solution vector space is converted into binary. Inside the problem if it has many variables then a different variable coding scheme is developed by arranging as many single variables coding as possible inside the problem [60]. This algorithm can process many solutions at a time. Using this algorithm many different elements of a population

can have a particular solution which is feasible. This is an instance of a result of a solution space and can be defined as an initial solution. This determines the selection of vigorous and impartial solutions, as it begins from many different ranges of points inside the solution space [61]. Later desired elements of a certain population are calculated to get the main objective function value. Using this principle, the significance function method can be used to convert a confined optimization problem to an unconfined one. It actually depends on what kind of problem we are solving. Later the objective function is used to get a fitness function that calculates a fitness value for each element of a particular population. This can be done using GA operators [55].

CHAPTER 4

RESULTS

Data Images

The techniques described in the methodology section were implemented using the MATLAB platform. These techniques are: Otsu's method, Iterative method, Maximum Entropy based method, Moment preserving, Balanced histogram thresholding, and Genetic algorithm. To evaluate the performance of these techniques and compare their efficiencies in detecting microcalcifications, 100 images were downloaded from different medical databases. These images are the results of screening breast cancer patients with X-ray, MRI, and Ultrasound technologies. They were classified depending on their qualities in 3 categories. Out of these 100 images 63 are very good quality images, 25 images are of good quality, and 12 are poor quality images.

Images classified as very good quality images contain microcalcification spots that have brighter intensity levels than the intensity levels of the background. The intensity levels of microcalcifications in these images are high enough to apply different image segmentation algorithms without any prior image enhancement. An example of this type of image is shown in Figure 4.1.

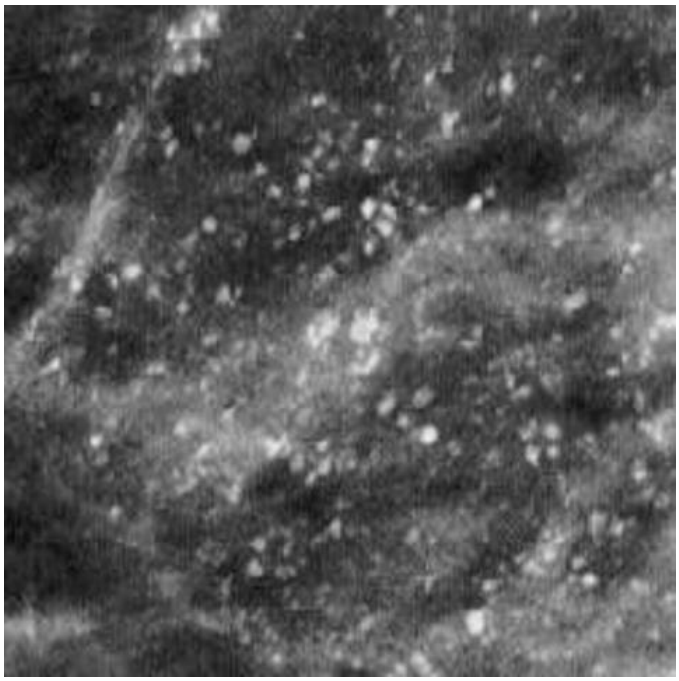

Figure 4.1: Example of very good quality image with microcalcifications.

Images classified as good quality images also contain microcalcification spots with brighter intensity levels than the background. For these images, the intensity levels of microcalcifications are slightly higher than the background levels. Thus, some of these images need enhancement before applying segmentation. An example of these types of images is shown in Figure 4.2.

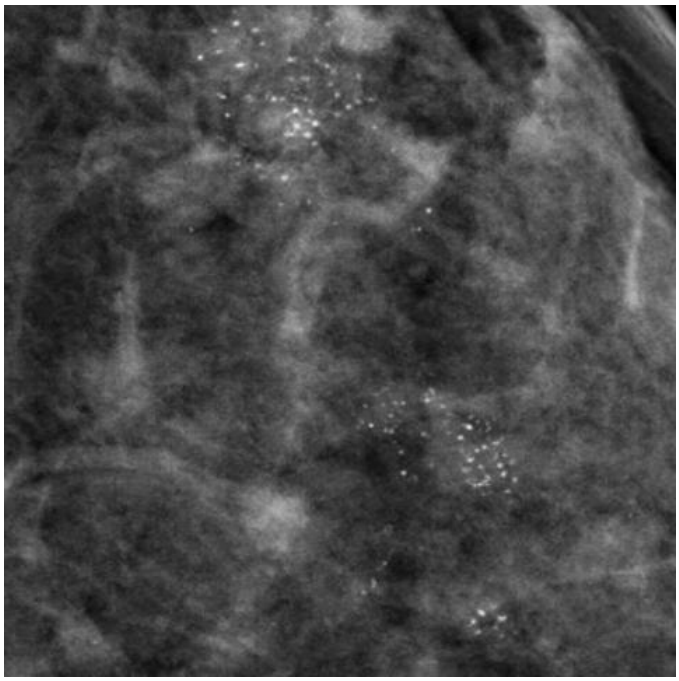

Figure 4.2: Example of good quality image with microcalcifications.

On the other hand, poor quality images are noisy, have non-uniform backgrounds, and the intensity levels of microcalcification spots are close to the background levels. Some images have dark backgrounds and other have bright backgrounds. This necessitates some prior image processing such as enhancement before isolating the microcalcifications. An example of this type of image is shown in Figure 4.3.

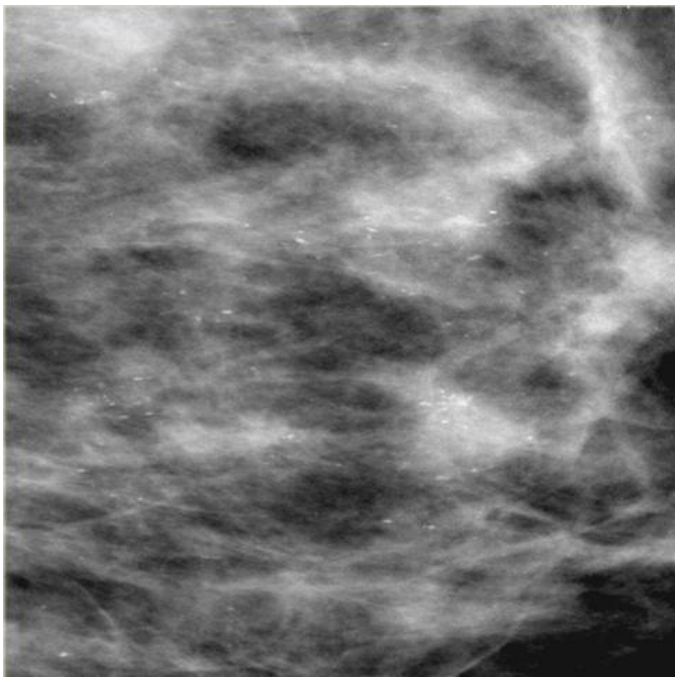

Figure 4.3: Example of poor quality image with microcalcifications.

For poor quality images and good quality images, image enhancement is used to increase the intensity levels of the microcalcification spots so that the background levels have much lower intensity levels. For very good quality images, image enhancement is not needed to isolate microcalcifications from the background [27].

Examples of results corresponding to image enhancement are shown in Figures 4.4 and 4.5. Figures 4.4 b) and 4.5 b) represent the output images after applying the image enhancement algorithm on the input images shown in Figures 4.4 a) and 4.5 a), repectively. From these images histograms, we can see that the pixels' intensity level of each output is stretched covering almost the entire range [0, 255] compared to the the pixels' intensity level of the original image due to the use of the image enhancement algorithm.

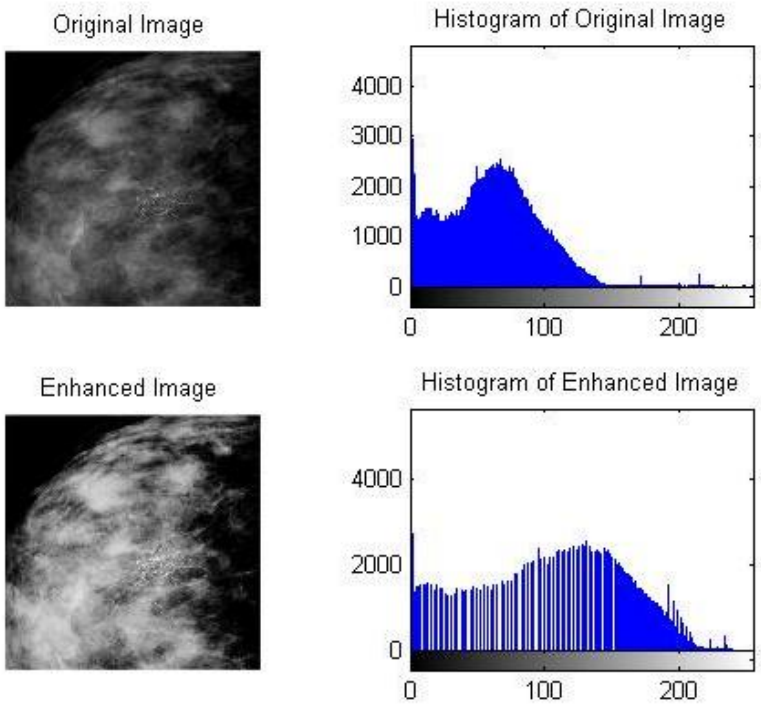

Figure 4.4: Original and enhanced images with their respective histograms.

From Figure 4.4 and 4.5, one can observe that the edge of the breast is sharper and the tissue is brighter than the background compared to those in the original images, which can help better in isolating the microcalcifications using the different thresholding methods.

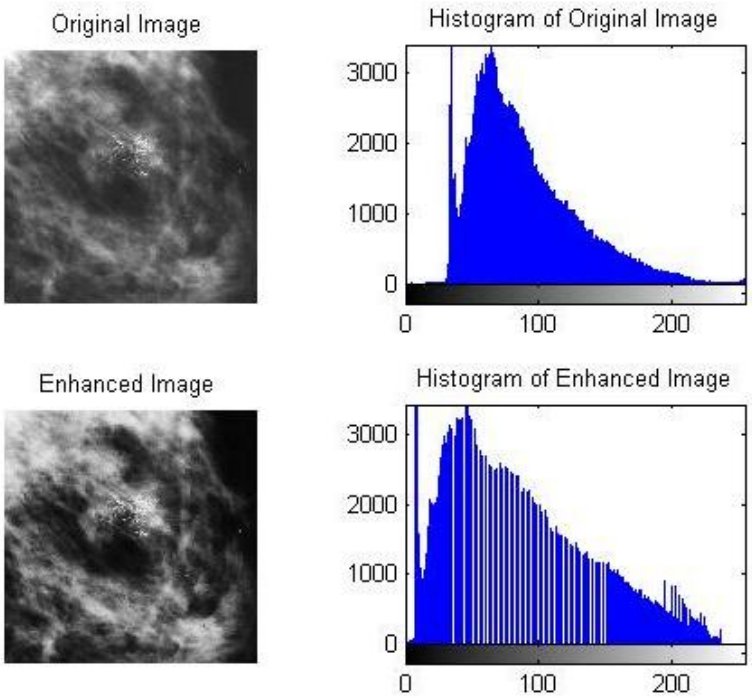

Figure 4.5: Original and enhanced images with their respective histogram.

The detection of breast microcalcifications using the different methods with results are described below.

4.1 Otsu's Method

We applied this method to all types of images to detect point microcalcifications. Examples of results are shown in Figures 4.6, 4.7, and 4.8. Figure 4.6 shows an example of a very good quality image and the output after applying Otsu's method. After applying Otsu's thresholding method, we can distinguish microcalcification spots separately from the background of the image.

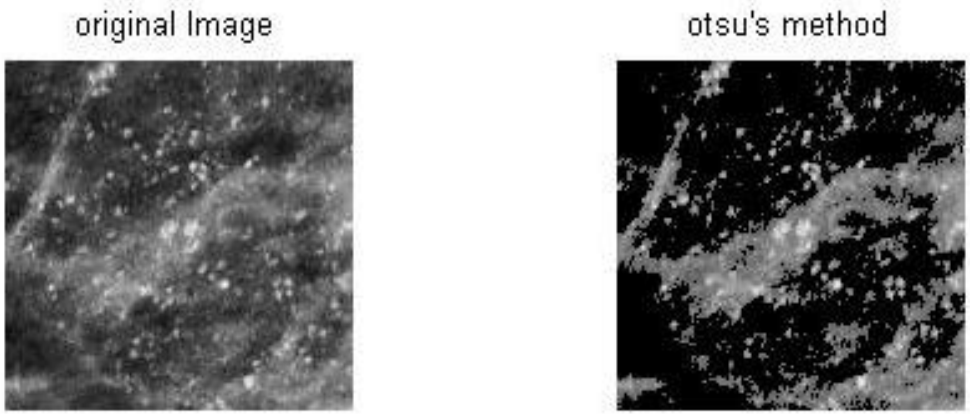

Figure 4.6: Microcalcifications detection for very good quality image using Otsu's method.

Figure 4.7 is an example of results corresponding to a good quality image, and shows the original image and the output after applying Otsu's method. The intensity levels of the microcalcification spots are slightly higher than the intensity level of the background, which makes it difficult to detect point microcalcificaitons in the original image.

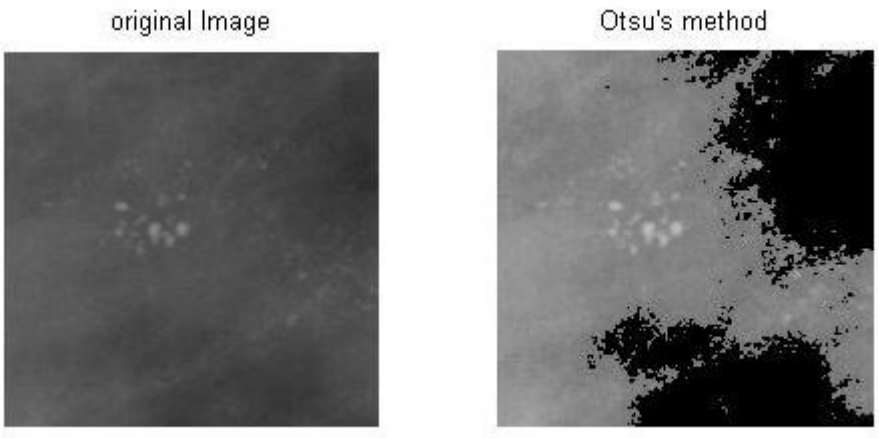

Figure 4.7: Microcalcifications detection for good quality image using Otsu's method.

Figure 4.8 is an example of a poor quality image for microcalcification detection. This figure shows the original image and the output after applying Otsu's method. The intensity levels of the

microcalcifications and the background are very close, which makes it difficult to detect point microcalcifications.

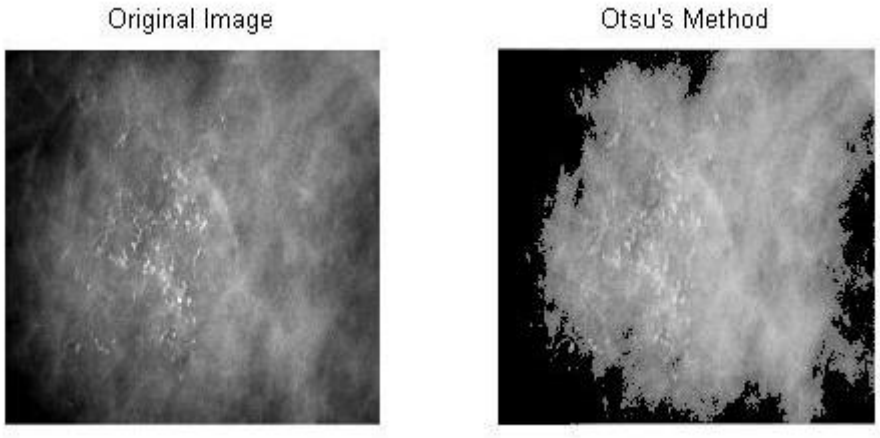

Figure 4.8: Microcalcifications detection for poor quality image using Otsu's method.

Table I shows that Otsu's method was able to detect point microcalcifications in 65% of very good quality images. For good quality images, this method was able to detect point microcalcifications in around 20% of the cases. However, for poor quality images, Otsu's method was able to detect point microcalcificaitons for only 8% of the cases.

Table I shows the results of 100 different types of images after applying Otsu's method.

Technique	Very good quality Images (63)	Good quality Images (25)	Poor quality Images (12)	Percentage very good quality images	Percentage good quality Images	Percentage poor quality image
Otsu's	41	5	1	65	20	8

4.2 Iterative Method

The segmentation process requires a threshold to separate a particular image into background and foreground. Proper selection of a threshold level significantly determines the output of the final results. In this section, we will discuss the results of the automated iterative thresholding method to determine the threshold level of images to detect point microcalcifications. The threshold level of a particular image was determined iteratively after considering the histogram and breast spatial resolution characteristics based on an image. No predetermined or experimental-based threshold value is needed. We applied this method to all types of images to detect point microcalcifications. Examples of results are shown in Figures 4.9, 4.10, and 4.11. Figure 4.9 shows an example of a very good quality image and the output after applying Iterative method. After applying Iterative thresholding method, we can distinguish microcalcification spots separately from the background of the image.

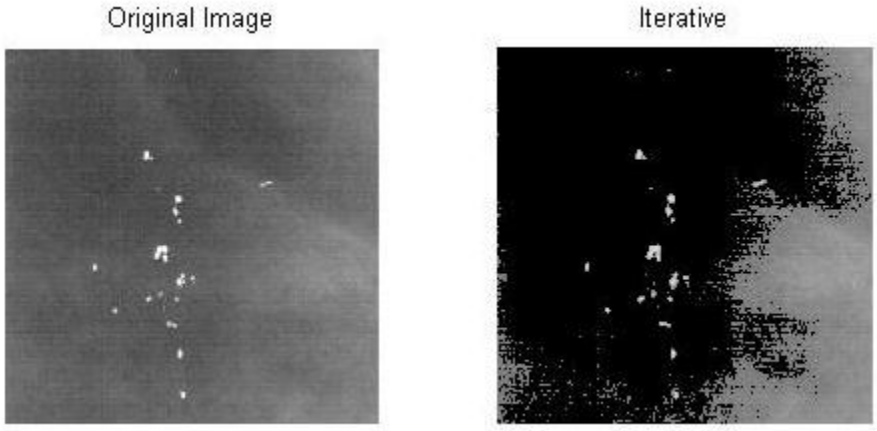

Figure 4.9: Microcalcification detection for very good quality image using Iterative method.

Figure 4.10 is an example of results corresponding to a good quality image. This Figure 4.10 shows the original image and the output after applying Iterative method. The intensity levels of the

microcalcification spots are slightly higher than the intensity level of the background, which makes it difficult to detect point microcalcifications in the original image.

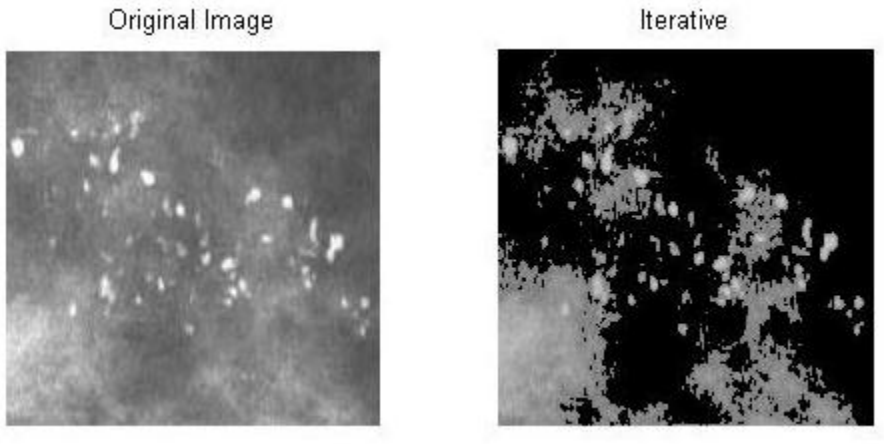

Figure 4.10: Microcalcifications detection for good quality image using Iterative method.

Figure 4.11 is an example of a poor quality image for microcalcification detection. This figure shows the original image and the output after applying Iterative method. The intensity levels of the microcalcifications and the background are very close, which makes it difficult to detect point microcalcifications.

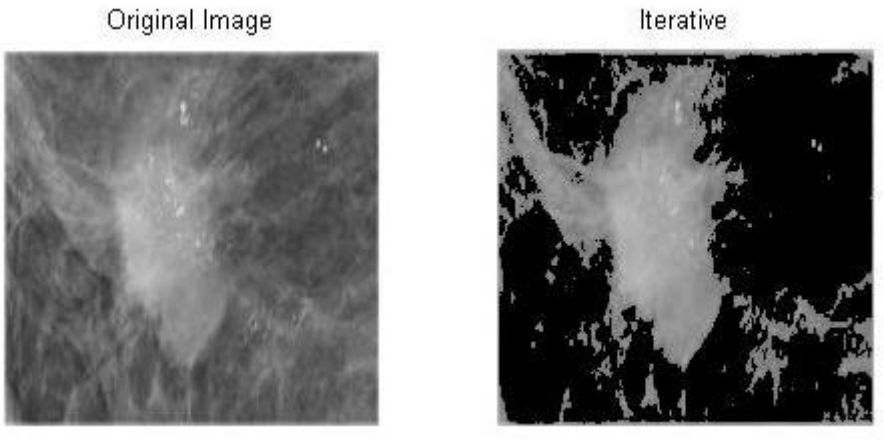

Figure 4.11: Microcalcifications detection for poor quality image using Iterative method.

The benefit of this iterative technique is that it can be utilized for different types of images without special necessity for image information data or operators' communication to adjust the desired threshold value. Data information of the current image are required to set the appropriate threshold value. In the beginning, we estimated local minimums of the image histogram using the algorithm. Proper selection of the threshold can differentiate between the foreground and background images at this local minimum. Moving forward from the lowest local minimum to the highest, our algorithm keeps evaluating until it has evaluated all local minimums and selects a proper local minimum. From Table II, we can see that for 63% of very good quality images, Iterative method was able to detect point microcalcifications. For good quality images, this method was able to detect point microcalcifications around 16% of the cases. However, for poor quality images, Iterative method was not able to detect point microcalcificaitons.

Table II shows the results of 100 different types of images after applying Iterative method.

Technique	Very good quality Images (63)	Good quality Images (25)	Poor quality Images (12)	Percentage very good quality images	Percentage good quality Images	Percentage poor quality Images
Iterative	40	4	0	63	16	0

4.3 Balanced Histogram Thresholding

Balanced histogram thresholding method is an automated image thresholding method for detecting point microcalcifications. We applied this method to all types of images to detect point microcalcifications. Examples of results are shown in Figures 4.12, 4.13, and 4.14. Figure 4.12 shows an example of a very good quality image and the output after applying Balanced histogram

thresholding method. After applying Balanced histogram thresholding method, we can distinguish microcalcification spots separately from the background of the image.

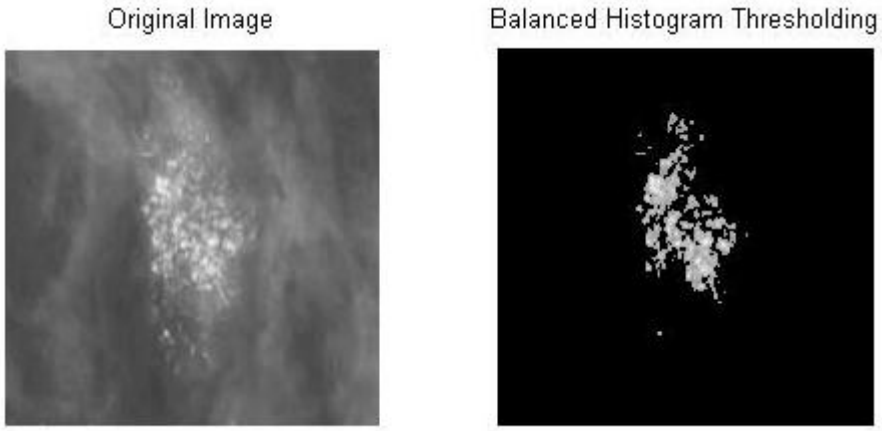

Figure 4.12: Microcalcifications detection for very good quality image using Balanced histogram thresholding method.

Figure 4.13 is an example of results corresponding to a good quality image. This Figure 4.7 shows the original image and the output after applying Balanced histogram thresholding method. The intensity levels of the microcalcification spots are slightly higher than the intensity level of the background, which makes it difficult to detect point microcalcifications in the original image.

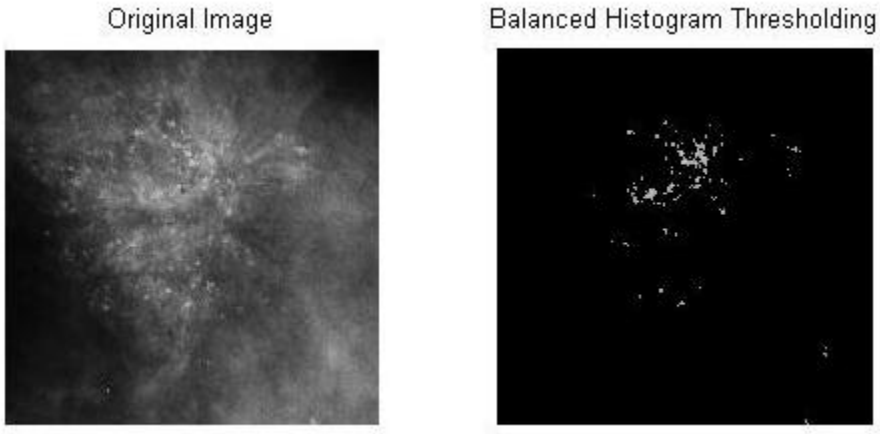

Figure 4.13: Microcalcification detection for good quality image using Balanced histogram thresholding method.

Figure 4.14 is an example of a poor quality image for microcalcification detection. This figure shows the original image and the output after applying balanced histogram thresholding method. The intensity levels of the microcalcifications and the background are very close, which makes it difficult to detect point microcalcifications.

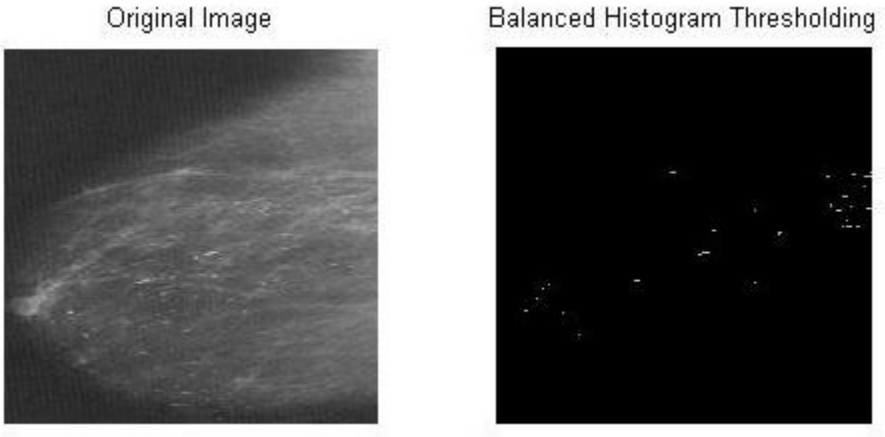

Figure 4.14: Microcalcification detection for poor quality image using Balanced histogram thresholding method.

From Table III we can see that, Balanced histogram thresholding method was able to detect point microcalcifications for 73% of very good quality images. For good quality images, this method was able to detect point microcalcifications for around 40% of the cases. However, for poor quality images Balanced histogram thresholding method was able to detect point microcalcifications for only 33% of images.

Table III shows the results of 100 different types of images after applying Balanced histogram thresholding method.

Technique	Very good quality Images (63)	Good quality Images (25)	Poor quality Images (12)	Percentage very good quality images	Percentage good quality Images	Percentage poor quality Images
Balanced	46	10	4	73	40	33

4.4 Moment Preserving

In this section, in order to detect point microcalcifications we applied Moment Preserving method as an image processing technique. Moment Preserving is another automated image segmentation method that keeps the moments of gray level distribution of the original image before and after thresholding. We applied this method to all types of images to detect point microcalcifications. Examples of results are shown in Figures 4.15, 4.16, and 4.17. Figure 4.15 shows an example of a very good quality image and the output after applying Moment Preserving method. After applying Moment preserving thresholding method, we can distinguish microcalcification spots separately from the background of the image.

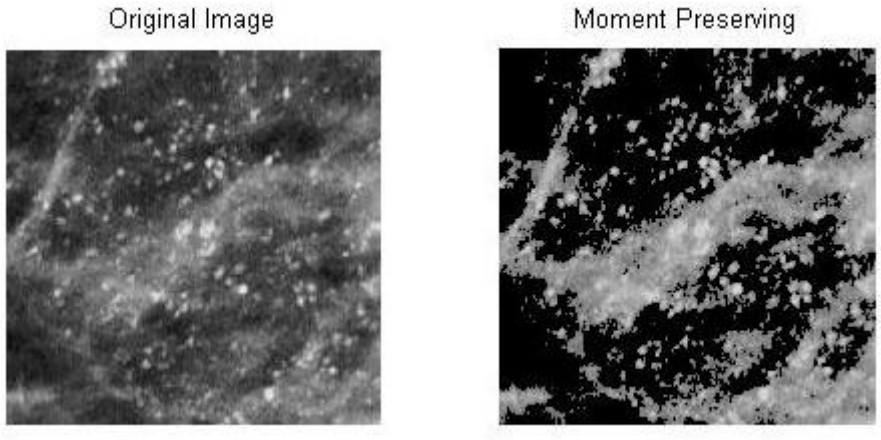

Figure 4.15: Microcalcification detection for very good quality image using Moment Preserving method

Figure 4.16 is an example of results corresponding to a good quality image and shows the original image, and the output after applying Moment Preserving method. The intensity levels of the microcalcification spots are slightly higher than the intensity level of the background, which makes it difficult to detect point microcalcifications in the original image.

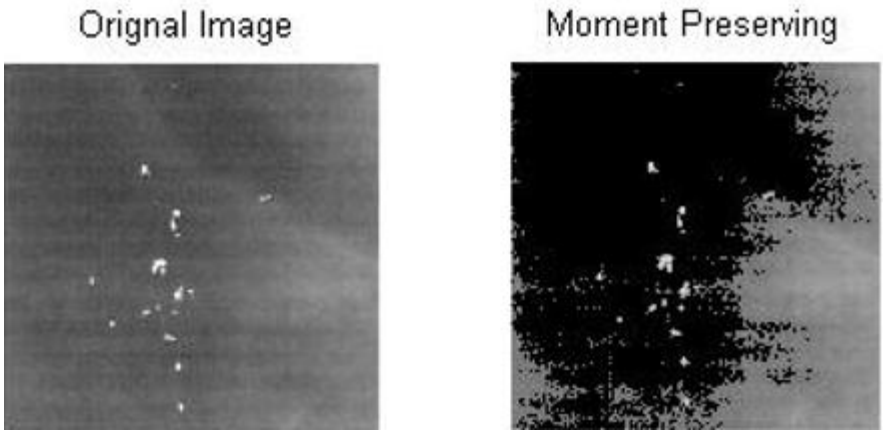

Figure 4.16: Microcalcification detection for good quality image using Moment Preserving method.

Figure 4.17 is an example of a poor quality image for microcalcification detection. This figure shows the original image and the output after applying Moment Preserving method. The intensity levels of the microcalcifications and the background are very close, which makes it difficult to detect point microcalcifications.

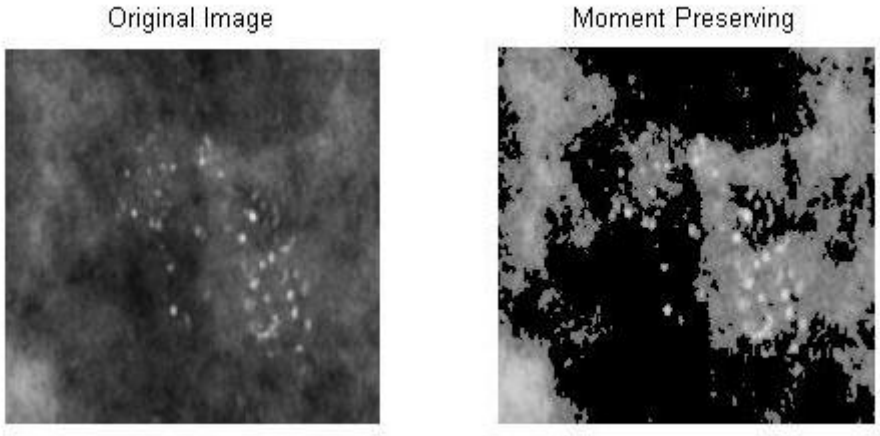

Figure 4.17: Microcalcification detection for poor quality image using Moment preserving method.

From Table IV we can see that Moment Preserving method was able to detect point microcalcifications for 65% of very good quality images. For good quality images, this method was able to detect point microcalcifications for around 24% of the cases. However, for poor quality

images Moment preserving method was able to detect point microcalcifications for only 16% of cases.

Table IV shows the results of 100 different types of images after applying Moment Preserving method.

Technique	Very good quality Images (63)	Good quality Images (25)	Poor quality Images (12)	Percentage very good quality images	Percentage good quality Images	Percentage poor quality Images
Moment Preserving	41	6	2	65	24	16

4.5 Maximum Entropy based method

In this section, we applied automated Entropy based method algorithm for the image segmentation process to detect microcalcifications. This method uses the entropy of the center and the neighboring area of the original image. We applied this method to all types of images to detect point microcalcifications. Examples of results are shown in Figures 4.18, 4.19, and 4.20. Figure 4.18 shows an example of a very good quality image and the output after applying Maximum Entropy based method. After applying Maximum Entropy based method, we can distinguish microcalcifications spots separately from the background of the image.

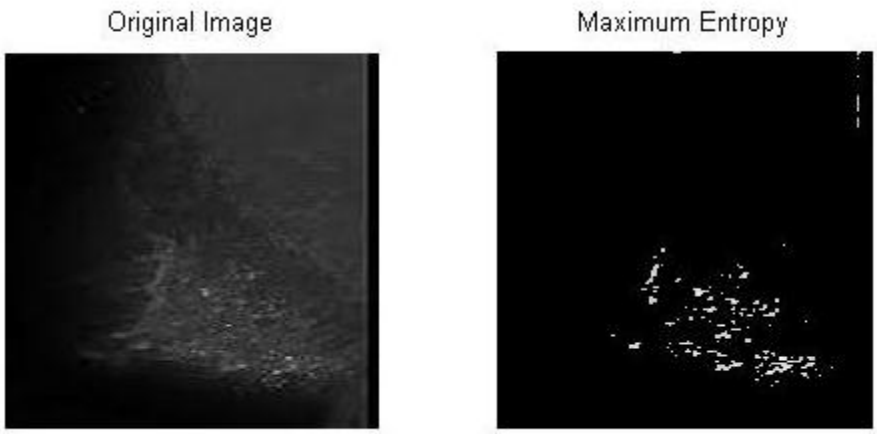

Figure 4.18: Microcalcification detection using Maximum Entropy based method.

Figure 4.19 is an example of results corresponding to a good quality image and shows the original image, and the output after applying this method. The intensity levels of the microcalcification spots are slightly higher than the intensity level of the background, which makes it difficult to detect point microcalcifications in the original image.

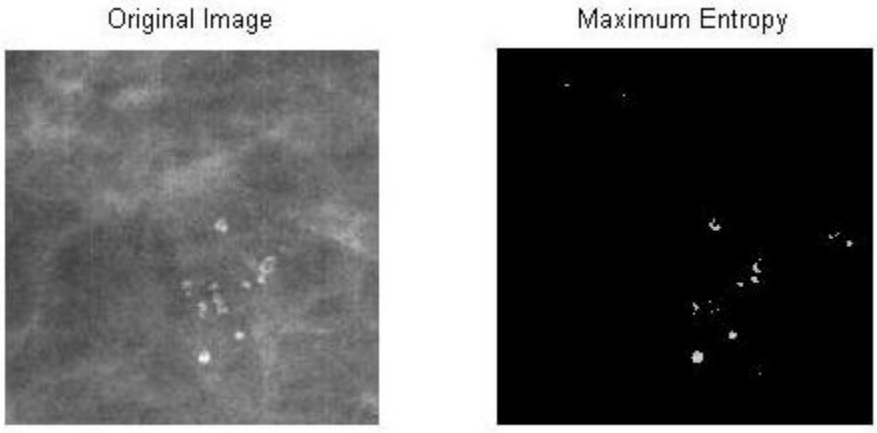

Figure 4.19: Microcalcification detection for good quality image using Maximum Entropy based method.

Figure 4.20 is an example of a poor quality image for microcalcification detection. This figure shows the original image and the output after applying Maximum Entropy based method. The intensity levels of the microcalcifications and the background are very close, which makes it difficult to detect point microcalcifications.

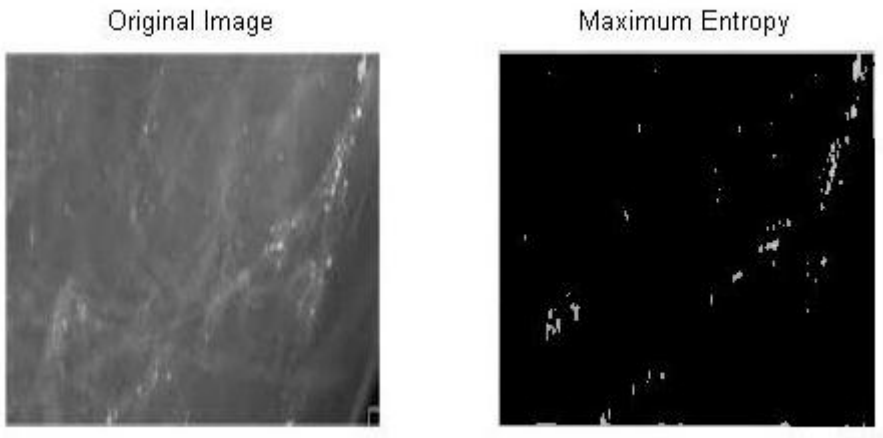

Figure 4.20: Microcalcification detection for poor quality image using Maximum Entropy based method.

In this method, an image is said to have reached its threshold when the addition of background and foreground image regions of a particular segmented area also have reached their maximum gray level, and both background and foreground of a particular image are considered as two different image sources. In images, foreground and background are considered as two different signal sources, so that when the sum of the two class entropies reaches its maximum, the image is said to have reached its optimum threshold. From Table V we can see that Maximum Entropy based method was able to detect point microcalcifications for 60% of very good quality images. For good quality images, this method was able to detect point microcalcifications for around 40% of the cases. However, for poor quality images Maximum Entropy method was able to detect point microcalcificaitons for only 25% of cases.

Table V shows the results of 100 different types of images after applying Maximum entropy based method.

Technique	Very good quality Images (63)	Good quality Images (25)	Poor quality Images (12)	Percentage very good quality images	Percentage good quality Images	Percentage poor quality Images
Maximum Entropy	38	10	3	60	40	25

4.6 Genetic Algorithm

In this section, we applied the automated Genetic Algorithm (GA) technique to detect point microcalcifications. In Genetic Algorithm several optimal threshold levels are selected for a particular image. Later on if the desired threshold level is not reached, then crossover is done to determine the selection of a better threshold, and this process is repeated until desired threshold value is obtained. We applied this method to all types of images to detect point microcalcifications. Examples of results are shown in Figures 4.21, 4.22, and 4.23. Figure 4.21 shows an example of a very good quality image and the output after applying Genetic Algorithm. After applying Genetic Algorithm, we can distinguish microcalcifications spots separately from the background of the image.

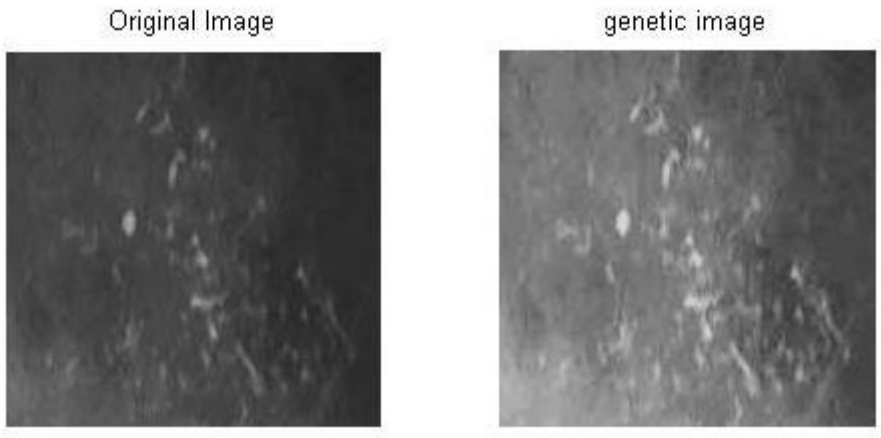

Figure 4.21: Microcalcification detection for very good quality image using Genetic Algorithm.

Figure 4.22 is an example of results corresponding to a good quality image and shows the original image, and the output after applying the Genetic Algorithm. The intensity levels of the microcalcification spots are slightly higher than the intensity level of the background, which makes it difficult to detect point microcalcifications in the original image.

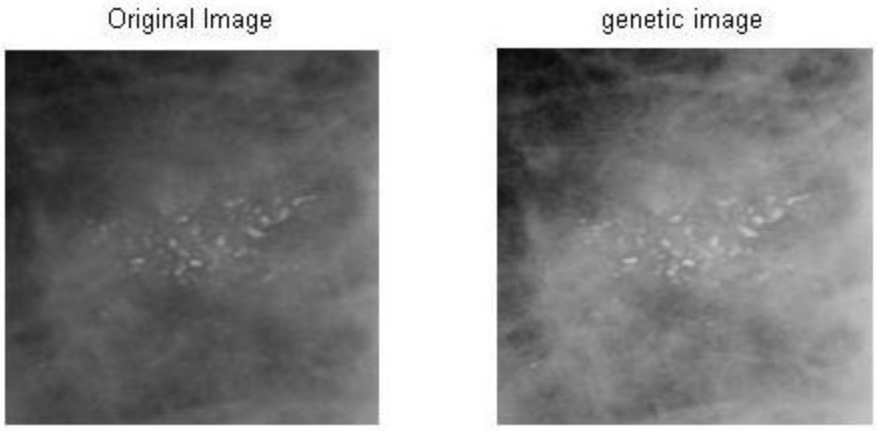

Figure 4.22: Microcalcification detection for good quality image using Genetic Algorithm.

Figure 4.23 is an example of a poor quality image for microcalcification detection. This figure shows the original image and the output after applying the Genetic Algorithm. The intensity levels

of the microcalcifications and the background are very close, which makes it difficult to detect point microcalcifications.

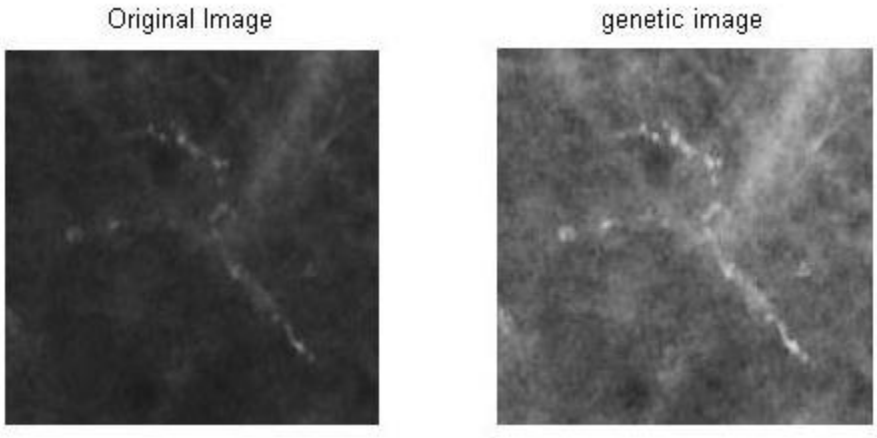

Figure 4.23: Microcalcification detection for poor quality image using Genetic Algorithm.

From Table VI, we can see that the Genetic Algorithm was able to detect point microcalcifications for 73% of very good quality images. For good quality images, this method was able to detect point microcalcifications in 32% of the cases. However, for poor quality images Genetic Algorithm was not able to detect point microcalcifications.

Table VI shows the results of 100 different types of images after applying Genetic Algorithm.

Technique	Very good quality Images (63)	Good quality Images (25)	Poor quality Images (12)	Percentage very good quality images	Percentage good quality Images	Percentage poor quality Images
Genetic Algorithm	46	8	0	73	32	0

CHAPTER 5

Efficiency Comparison of the Image Processing Techniques

Segmentation or thresholding algorithm methods can be classified into two different types, analytical methods and empirical methods [62]. By examining the principles and properties analytical methods assess thresholding algorithms. On the other hand, empirical methods assess the thresholding algorithms by implementing them on images and by assessing the quality of the results.

Though analytical methods are better than empirical methods, by avoiding the influence created by the arrangement of evaluation experiments, there were not many analytical methods available in the literature. Many different types of empirical methods were suggested in the past. Normally, the empirical methods can be divided into two main types. Those are goodness methods and discrepancy methods [62].

The goodness methods measure the segmented images depending on human intuition about what circumstances should be considered by an "ideal" segmentation. The human intuition assessment is mathematically defined by equations, so the "goodness" can be quantitatively measured by simply computing these measures. Therefore, these goodness methods can assess the algorithms by using the segmented images themselves without reference to the ideal images.

The discrepancy methods measure the inequality between an actually segmented image and a correctly/ideally segmented image. Both images can be gathered from the same input image. In

some cases, if images are synthetic images, the reference images can be simply gathered from the image generation procedure, while in some cases where the test images are real images, manually (with the help of visual inspection) segmented images are often used as references [62].

In this dissertation, we have performed the comparison of the different segmentation techniques using a goodness method: visual inspection.

Figures 5.1-5.4 gives examples of side by side comparisons.

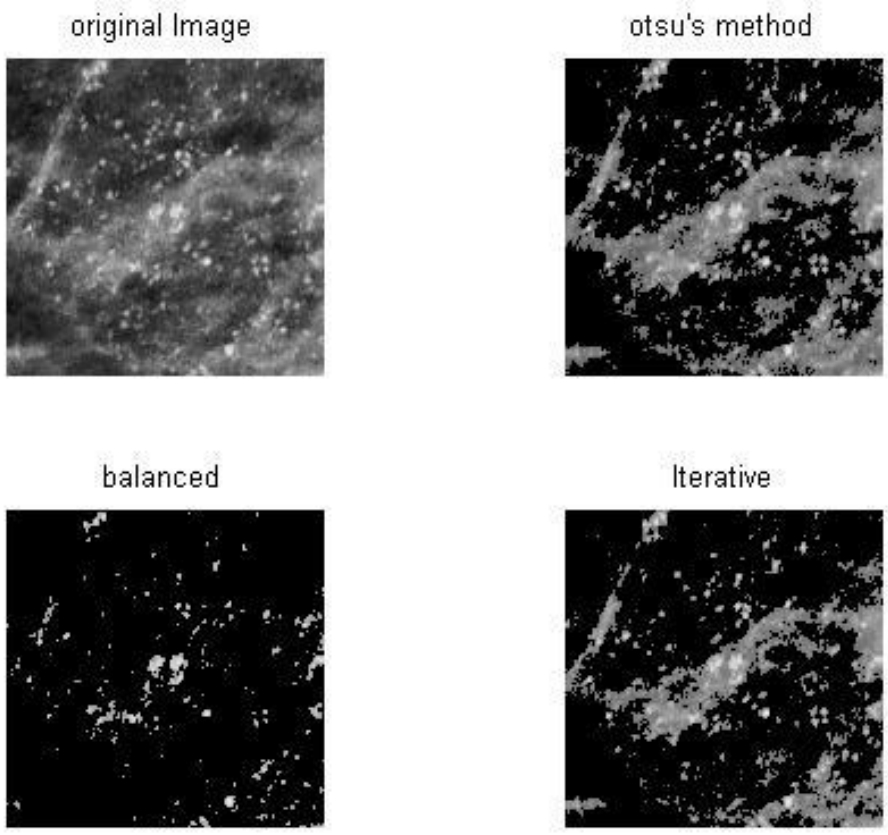

Figure 5.1: Microcalcifications detection for very good quality image using Otsu's, Balanced, and Iterative method.

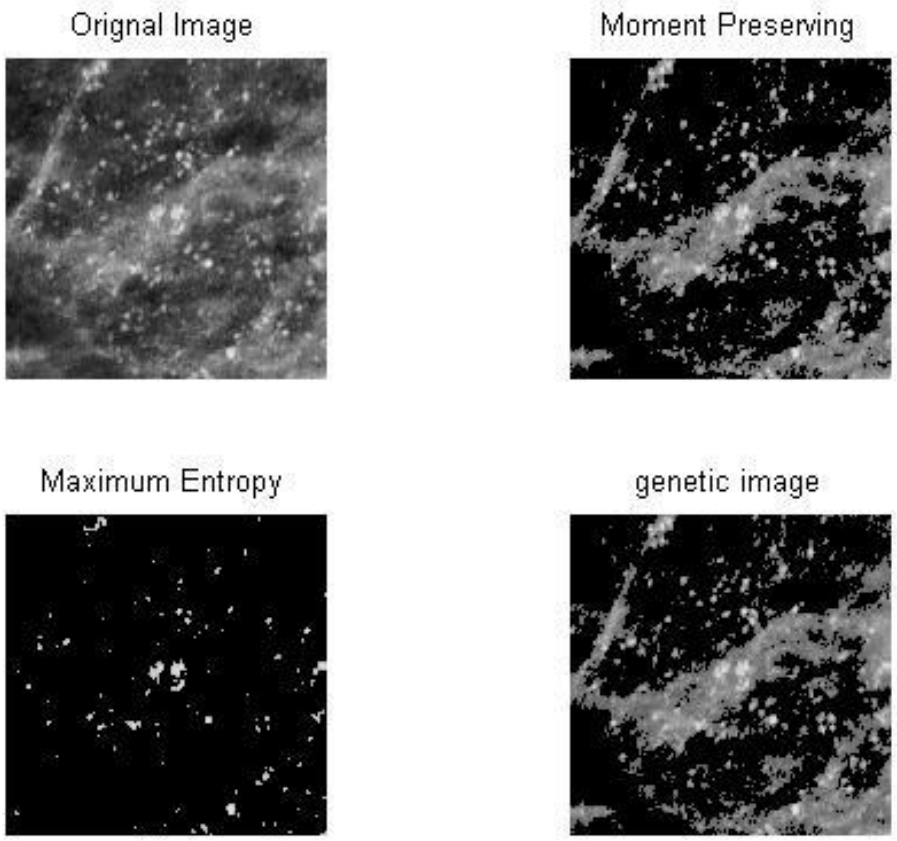

Figure 5.2: Microcalcifications detection for very good quality image using Moment Preserving, Maximum Entropy, and Genetic Algorithm.

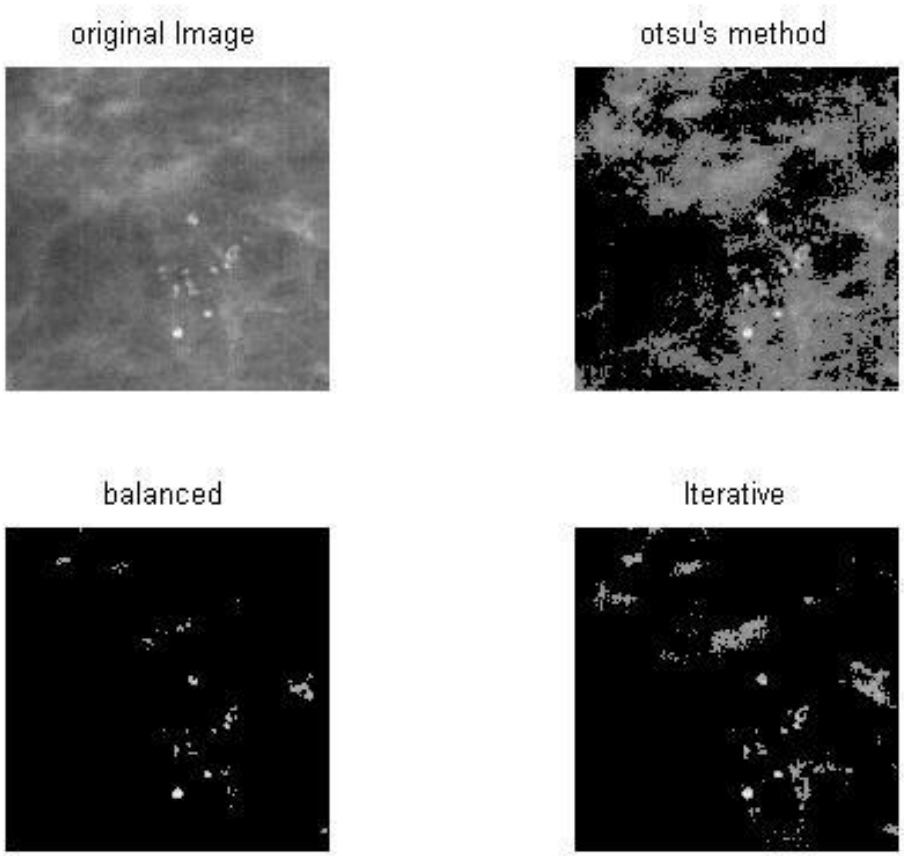

Figure 5.3: Microcalcifications detection for good quality image using Otsu's, Balanced, and Iterative method of another image.

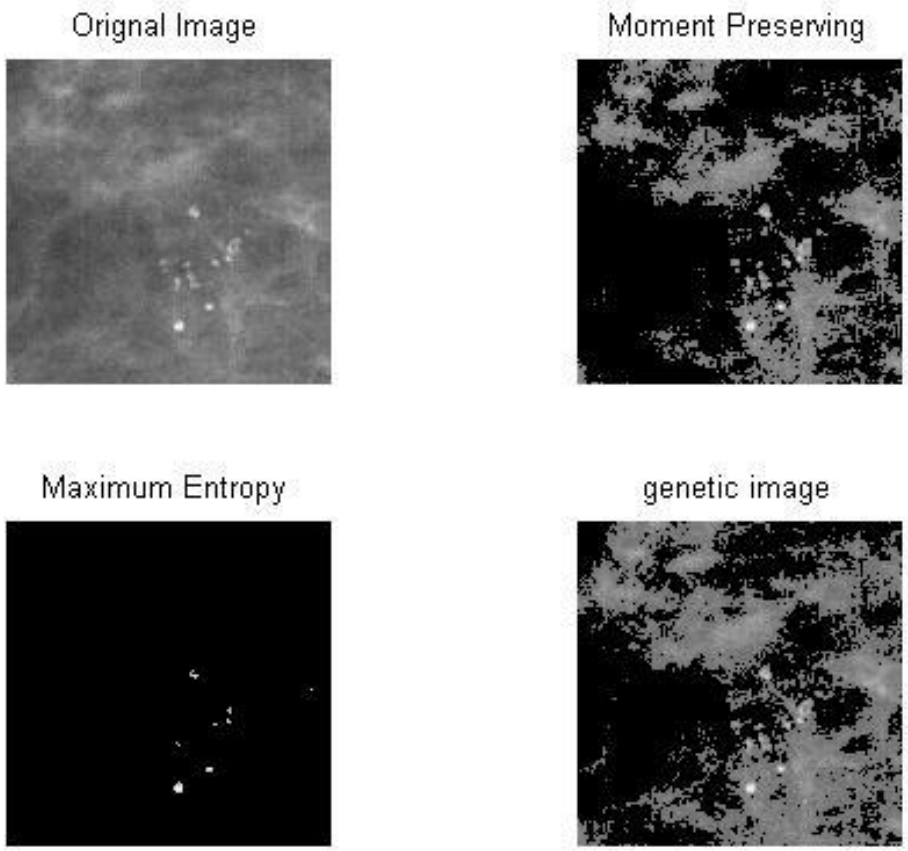

Figure 5.4: Microcalcifications detection for good quality using Moment Preserving, Maximum Entropy, and Genetic Algorithm of another image.

After analyzing 100 different images, we found that Balanced histogram thresholding works the best for image segmentation with around 73% efficiency for very good quality images, 40% efficiency for good quality images and 33% efficiency for poor quality images.

We also got better efficiency for microcalcification detection using the Genetic Algorithm with 73% of efficiency for very good quality images and around 32% for good quality images. However, the detection rate was 0% for poor quality images.

The efficiency of Moment Preserving method was 65% for very good quality images and around 24% for good quality images, and around 16% for poor quality images. Compared to other thresholding techniques, this technique is not the best to detect point microcalcifications, but for some images it gave very good results compared to other techniques for detecting point microcalcifications. The efficiency of Otsu's method was 65% for very good quality images and around 20% for good quality images, and around 8% for poor quality images. The efficiency of Iterative method was 63% for very good quality images and around 16% for good quality images, and around 0% for poor quality images. Finally, the efficiency of Maximum entropy method was 60% for very good quality images and around 40% for good quality images, and around 25% for poor quality images.

Table VII Comparison table after applying different thresholding techniques

Techniques	Very good quality image (63)	Good quality image (25)	Poor quality image (12)	Percentage very good quality image	Percentage good quality image	Percentage poor quality image
Otsu's	41	5	1	65%	20%	8%
Balanced	46	10	4	73%	40%	33%
Iterative	40	4	0	63%	16%	0
Moment Preserving	41	6	2	65%	24%	16%
Maximum Entropy	38	10	3	60%	40%	25%
Genetic Algorithm	46	8	0	73%	32%	0

As one can see, for very good quality images both the Balanced Histogram and Genetic Algorithm algorithms have a detection rate of 73%. These are followed by the Otsu's method and Moment Preserving algorithm. Iterative method has a detection rate of 63% and Maximum Entropy has the least detection rate of 60%. For good quality images both the Balanced Histogram and Maximum Entropy algorithms have a detection rate of 40%. These are followed by the Otsu's method and Moment Preserving method with the detection rate of 20% and 24% respectively. The Genetic Algorithm has a detection rate of 32% and Iterative method has the least detection rate of 16%. For poor quality images Otsu's method and Balanced Histogram Thresholding method have the detection rate of 8% and 33% respectively. Moment Preserving and Maximum Entropy also have the detection rate of 16.7% and 25% respectively. The Iterative and Genetic algorithm were not able to detect microcalcifications for poor quality images at all.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

In this dissertation we explained, developed and experimented with different image processing techniques that can be used for the early detection of breast cancer by detecting point microcalcifications. In this chapter we will summarize our research and briefly discuss some areas that merit future research.

Research Summary

In Chapter 1, we discussed the significance of breast cancer and the necessity of early detection and why it's so important to detect, and prevent this disease in its early stage. We also discussed our objectives and approach to the early detection of breast cancer.

In Chapter 2, we discussed the state of the art of different techniques used for the early detection of breast cancer. We also discussed the efficiency and impact of those techniques on breast cancer detection. We also discussed signal and image processing techniques used by other researchers for microcalcifications detection.

In Chapter 3, we discussed the methodologies and theories of several techniques used in this dissertation for early detection of breast cancer by detecting point microcalcifications. These techniques are: Otsu's method, Iterative method, Maximum Entropy based method, Moment Preserving, Balanced Histogram Thresholding, and Genetic Algorithm.

In chapter 4, we discussed the results of our research. The size of the microcalcifications ranges from 0.1mm to 0.5mm, and average 0.3 mm. in size. Because of their small size, detection of microcalcifications requires proper implementation of different techniques. For some images with low grayscale background level, image enhancement was used to get better resolution so that image segmentation can be done more efficiently to detect point microcalcifications. When applying image enhancement, we should not enhance the image too much, otherwise it will be difficult to do proper image segmentation to detect microcalcifications. The brightness of microcalcifications and other neighboring tissues can become too high making it difficult to distinguish breast tissue and microcalcifications separately.

After image processing, we compared the output results to find a better way to detect point microcalcifications for early detection. In order to evaluate the performance of different image processing techniques, we compared those techniques on 100 images. For some, image processing techniques worked very well and for other images some techniques did not work well. So, it is challenging to select a specific technique that can be used for image segmentation. Rather, applying different image and signal processing techniques together for varying circumstances and different images can be a good approach to detect point microcalcifications.

After implementing each image processing technique, we applied other techniques as well to the original images to see the efficiency of different techniques for 100 images. We initially validated the output results from the applied image processing algorithms by applying those techniques to very good, good, and poor quality images.

Our results show that the Balanced Histogram method and the Genetic Algorithm are good for detecting point microcalcifications for very good quality images. For good quality images,

Balanced Histogram and Maximum Entropy are efficient in detecting point microcalcifications. Only Balanced Histogram Thresholding is good for detecting point microcalcifications for poor quality images.

Compared with other image processing techniques, our results show that Balanced Histogram method is the best method because the success rate of using this technique is above 73% for very good quality images. It also has the highest success rate, 40% for good quality images and a 33% success rate for poor quality images. Although it was not able to detect point microcalcifications for some images, its efficiency is more acceptable and can be considered a better image processing technique for detecting point microcalcifications compared to the other techniques. Our results also show that using just one single method does not yield the desired output. However, using a combination of all these image processing techniques, microcalcifications can be detected more efficiently.

Future work

As shown in this dissertation, thresholding techniques efficiency is limited because of all the problems affecting medical images containing microcalcifications. Furthermore, these image processing techniques cannot detect microcalcifications if they are not visible in the image. To improve the detection of these spots, techniques that process the sensors' signals are more suitable. One of these techniques is the Time-reversal (TR) imaging with Multiple Signal Classification (TR-MUSIC) algorithm developed by Devaney [63] and that can be used to increase the resolution of ultrasound images. Time-reversal (TR) methods have recently received a lot of interest in the ultra-sound medical imaging community [64]. TR-MUSIC combines TR focusing with the MUSIC signal-subspace technique to increase the resolution of ultrasound images [65]. TR-

MUSIC algorithm was investigated during this research project. Several parameters on the TR-MUSIC efficiency, such as sound speed, sampling frequency, Eigenvalue, and number of traces can be examined to increase the resolution of ultrasound images [66]. One of the major limitations of TR-MUSIC algorithm is that it's efficient for homogeneous medium. More investigation is required considering this algorithm for non-homogeneous medium to apply this technique for early detection of breast cancer.

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APPENDIX

Evaluation of TR-MUSIC Algorithm Efficiency in Detecting Breast Microcalcifications

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Abstract - **Early detection is the key surviving from breast cancer. The earliest indication of potential breast cancer detectable by current screening methods is the presence of microcalcifications (MCs). The low detection rate of MCs with ultrasound is due to the low spatial resolution of the ultrasound images and to the presence of speckle noise, which masks the tiny microcalcifications. This paper aims to investigate the efficiency of the time reversal multiple signal classification (TR-MUSIC) algorithm in detecting breast microcalcifications. Experiments were performed on numerical phantoms, and results show that the TR-MUSIC algorithm efficiency depends on several parameters.**

Keywords- Breast cancer, microcalcifications, TR-MUSIC algorithm, sampling frequency, sound speed.

I. INTRODUCTION

Breast cancer is the most common non-skin malignancy in women and the second leading cause of female cancer mortality [1]. Women in the United States have one of the highest incidence rates of breast cancer in the world, with about 230,400 new cases of breast cancer diagnosed and 39,500 women dying each year [2]. Men are also affected by this disease. The American Cancer Society estimates that in 2012 about 2,190 new cases of invasive breast cancer will be diagnosed among men in the United States [3]. Although the incidence of breast cancer in men is less common, men with breast cancer have significantly lower survival rates than women [4]. Since the causes of this disease are not all known, primary prevention seems impossible. Therefore, early detection is the major key to surviving this disease.

The earliest indication of potential breast cancer is the presence of microcalcifications (MCs), which are small crystal calcium apatite that form in breast tissue through a number of mechanisms [5]. MCs range in size from 100 µm single crystals to clusters up to several centimeters in diameter [6]. MCs are the first sign of breast cancer in more than half of all breast cancer cases and they are sometimes the only indication of malignancy [7], making their detection critical.

Currently, X-ray mammography is the only accepted method for detecting breast MCs. However, this imaging modality presents several disadvantages and limitations. Mammography exposes the subject to ionizing radiation and is relatively ineffective in w omen with dense breasts [8]. Additionally, mammography is uncomfortable and sometimes painful because the breast must be compressed between flat surfaces to improve image quality. Moreover, only around 10–25% of mammographically suspicious lesions are found to be malignant from tissue biopsy, resulting in unnecessary and costly biopsy procedures.

Ultrasound imaging, on the other hand, is a non-ionizing technique and thus could be a safer method for breast MC detection. However, current state-of-the-art clinical ultrasound scanners cannot reliably detect MCs in the size range of clinical interest (0.1-0.5 mm) [9]. The low detection rate of MCs with ultrasound is due to the low spatial resolution of the ultrasound images and to the presence of speckle noise, which masks the tiny MCs [10].

Time-reversal (TR) methods have recently received a lot interest in the ultra-sound medical imaging community [11, 14]. One of these techniques is the Time-reversal (TR) imaging with Multiple Signal Classification (TR-MUSIC) algorithm developed by Devaney [11, 12]. TR-MUSIC combines TR focusing with the MUSIC signal-subspace technique to increase the resolution of ultrasound images [13, 14].

This paper investigates the impacts of sound speed and sampling frequency on the efficiency of the TR-MUSIC algorithm in detecting MCs. In section II, the TR-MUSIC

algorithm is explained. Section III gives and discusses examples of results.

II. TR-MUSIC ALGORITHM

Consider an array of N ultrasound transducers interrogating a medium containing M point scatters (much smaller than ultrasound wavelength) such that $M < N$. Each transducer is excited sequentially and the scattered signals are measured by all transducers, yielding the inter-element response matrix $K_{ij}(\omega)$ of the array at the angular frequency ω, with subscripts i and j ranging from 1 to N. Under the Born approximation, the matrix K is given by,

$$K = |F(\omega)|\, e^{i\phi(\omega)} \sum_{m=1}^{M} \gamma_{\kappa}(\mathbf{r_m}) G(\mathbf{r_m}, \omega) G^{T}(\mathbf{r_m}, \omega) \qquad (1)$$

where $F(\omega)$ combines the transfer function of the emitted pulse and the electromechanical responses of the transducer elements, assuming all elements have the same characteristics. The phase response of $F(\omega)$ is $\varphi(\omega)$. The fluctuation function is a measure of the reflectivity of the scatters. In the case of uniformly-excited planar transducers, the elements of the vector are the integrals of the Green's function over the surfaces of the transducers:

$$G^{T}(\mathbf{r_m}, \omega) = \left[\iint_{S_1} \frac{\exp[-ik|\mathbf{r_m} - \mathbf{r}'|]}{4\pi|\mathbf{r_m} - \mathbf{r}'|} d\mathbf{r}', \ldots, \iint_{S_N} \frac{\exp[-ik|\mathbf{r_m} - \mathbf{r}'|]}{4\pi|\mathbf{r_m} - \mathbf{r}'|} d\mathbf{r}' \right], \qquad (2)$$

Where S_j is the surface area of the j^{th} transducer, $k = \omega/c - i\alpha$ is the complex wave number, α is the amplitude attenuation coefficient of the medium, c is the average sound speed, and i is the imaginary unit. It is clear that the matrix K is symmetric and maps C^n, the vector space of complex N-tuples, to the subspace S_0 spanned by the vectors $G(\mathbf{r_m}, \omega)$; that is,

$$\mathrm{S}_0 = \mathrm{Span}\{G(\mathbf{r_m}, \omega),\ m = 1, 2, \ldots, M\}. \qquad (3)$$

The MUSIC algorithm is based on the singular-value decomposition (SVD) of the matrix K written in the form,

$$K v_p = \sigma_p u_p, \qquad K^{\dagger} u_p = \sigma_p v_p,$$
$$K = \sum_{p=1}^{N} \sigma_p u_p v_p^{\dagger}, \qquad (4)$$

respectively. It was shown by Devaney [11] that the vectors $G(\mathbf{r_m}, \omega)$ evaluated at the scatterer locations form a basis for S_0. Therefore, the signal singular vectors (vectors with non-zero singular values) of the matrix K can be represented in matrix form as,

$$U_{sig}(\omega) = [u_1 \ \ u_2 \ldots \ u_M] = e^{\frac{i\phi(\omega)}{2}} \left[\frac{G(\mathbf{r}_1, \omega)}{\|G(\mathbf{r}_1, \omega)\|} e^{i\beta_1} \ \ \frac{G(\mathbf{r}_2, \omega)}{\|G(\mathbf{r}_1, \omega)\|} e^{i\beta_2} \ \ \ldots \ \ \frac{G(\mathbf{r}_M, \omega)}{\|G(\mathbf{r}_M, \omega)\|} e^{i\beta_M} \right]$$

$$V_{sig}(\omega) = [v_1 \ \ v_2 \ \ \ldots \ \ v_M] = e^{\frac{-i\phi(\omega)}{2}} \left[\frac{G^*(\mathbf{r}_1, \omega)}{\|G(\mathbf{r}_1, \omega)\|} e^{i\beta_1} \ \ \frac{G^*(\mathbf{r}_2, \omega)}{\|G(\mathbf{r}_2, \omega)\|} e^{i\beta_2} \ldots \ \ \frac{G^*(\mathbf{r}_M, \omega}{\|G(\mathbf{r}_M, \omega)\|} e^{i\beta_M} \right]$$

Where the superscript * denotes the complex conjugate. The SVD analysis of a complex-valued matrix is non-unique by an arbitrary phase. The phase angle in the equation above represents this non-uniqueness.

III. RESULTS

TR-MUSIC algorithm outputs are impacted by several parameters, including sound speed, sampling frequency, and number of traces. This paper investigates the impacts of sound speed and sampling frequency on the efficiency of the TR-MUSIC algorithm in detecting MCs. Numerical phantoms that mimic breasts with random distributions of microcalcifications were developed and used. An array of 124 transducers was assumed for these experiments. The MCs were randomly distributed, and their number was less than the number of transducers. The TR-MUSIC algorithm only works when the number of scatters is smaller than the number of transducers.

To investigate the impact of the sampling frequency on the MUSIC output, the sound speed was set to 1540 m/s and the algorithm was executed for several sampling frequencies ranging from 25 MHz to 41 MHz. Figs. 1 to 3 shows the results of changing the sampling frequency. For low frequencies, figures show long-tailed scatters that illustrated how the sound waves are reflected inside the phantoms. As expected, the size of these scatters decreases when the sampling frequency increases; thus, point MCs become more distinguishable with increasing sampling frequencies. MCs are more detectable at a frequency of 41 MHz. Therefore, the proper selection of sampling frequency is very important when using the TR-MUSIC algorithm on ultrasound images.

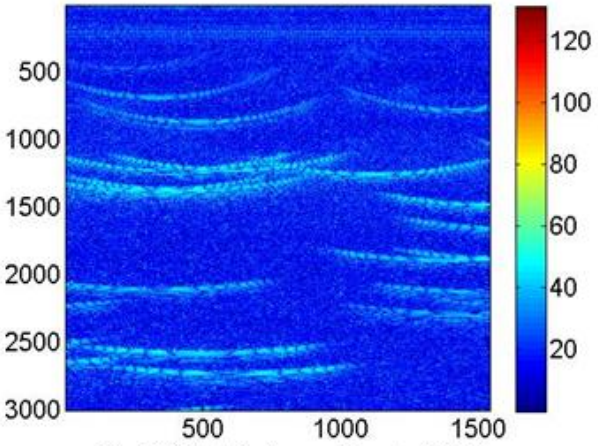

Fig.1. MC detection for a sampling rate of 25 MHz

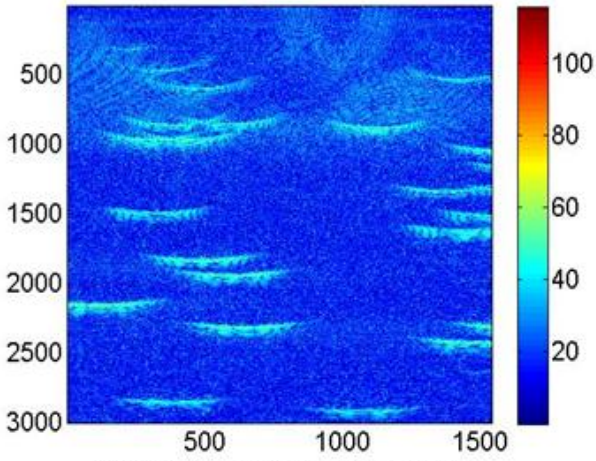

Fig.2. MC detection for a sampling rate of 35 MHz.

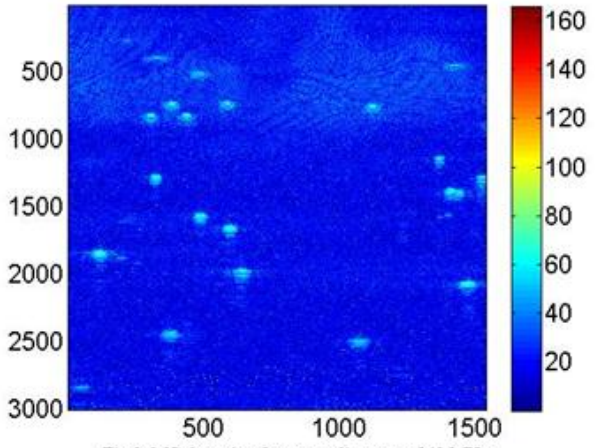

Fig.3. MC detection for a sampling rate of 41 MHz

The impact of the sound speed on the efficiency of the TR-MUSIC algorithm was also investigated. For these experiments, the sampling frequency was set to 41MHz, and the sound speed was varied from 1380 m/s to 1540 m/s. Examples of results are shown in Figs. 4 and 5. As expected, point MCs are more scattered for low sound speeds, as shown in Fig. 4. However, they are more distinguishable for a sound speed of 1540 m/s, as shown in Fig. 5. One possible reason is that the penetration of the sound waves increases as its velocity increases. Therefore, proper selection of sound speed is also very important when using the TR-MUSIC algorithm on ultrasound images.

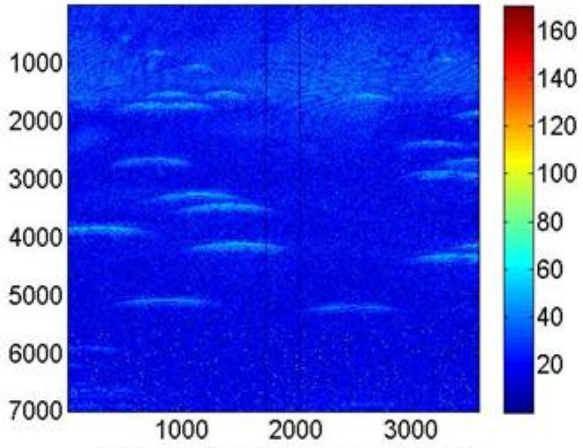

Fig.4. MC detection for a sound speed of 1380 m/s.

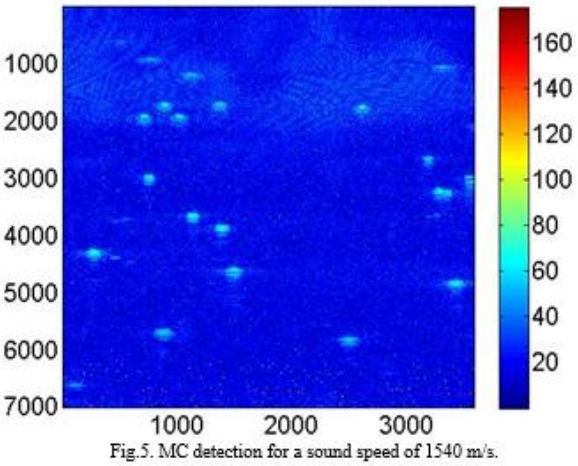

Fig.5. MC detection for a sound speed of 1540 m/s.

IV. CONCLUSION

This paper investigates the impact of sampling frequency and sound speed on the efficiency of the TR-MUSIC algorithm. Experiments were performed using numerical phantoms that mimic breasts with MCs. Frequency sampling rates varied from 25 MHz to 41 MHz, and sound speeds varied from 1380 m/s to 1540 m/s. As expected, results show that the quality of images produced by the TR-MUSIC algorithms increases with increasing sampling frequency and sound speed. The best results were obtained for a sampling frequency of 41 MHz and a sound speed of 1540 m/s.

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A Survey of Medical Imaging Techniques Used for Breast Cancer Detection

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Abstract-In this survey paper, we explored different medical imaging techniques used in the diagnosis of breast cancer. We compared their effectiveness, advantages, and disadvantages for detecting early-stage breast cancer. We mainly focused on X-ray mammography, ultrasound, and magnetic resonance imaging (MRI), as they are the primary imaging modalities used in the clinic for the diagnosis of breast cancer.

***Keywords*—X-ray Mammography, Ultrasound Imaging, Magnetic Resonance Imaging (MRI), Breast Cancer**

I. INTRODUCTION

According to the American cancer society, breast cancer is the second highest cause of mortality among women in the US [1]. In 2013, over 232,000 women in America will be newly diagnosed with breast cancer, and more than 39,000 women will die from this disease [1]. Breast cancer death rates generally increase with age. 95% of new cases and 97% of breast cancer deaths occur in women 40 years of age and older [2].

X-ray mammography was originally the only accepted imaging modality for detecting breast cancer [3]. However, X-ray mammography is not reliable for imaging patients with dense breasts. Furthermore, X-ray mammography exposes patients to ionizing radiations. In recent years, new imaging techniques have been used to complement X-ray mammography and overcome some of its limitations and disadvantages. Nowadays, X-Ray mammography, ultrasound, and magnetic resonance imaging (MRI) are imaging modalities routinely used to screen for breast cancer.

The American cancer society recommends that patients with a family history of breast cancer or who are more vulnerable to the disease due to other factors be screened annually beginning age 40, or 10 years before the age of diagnosis of a first-degree relative [1]. When screening high risk women, the overall detection rate of mammography is 36% and the combined detection rate of mammography and MRI is 92.7% [4]. mammography and ultrasound id 52%, compared with 92.7% of combined mammography and MRI [4]. Therefore, the combined effectiveness for detecting breast cancer with mammography, ultrasound, and MRI is much higher than that of only one of these imaging techniques.

When breast cancer is diagnosed, an ultrasound or MRI guided biopsy can confirm the cancer. In many cases, ultrasound-guided biopsy is preferred because of its lower cost, relative ease, and higher degree of patient comfort. Several treatment options are available after the diagnosis of breast cancer. The most common treatment is breast mastectomy, which removes cancerous tissues and prevents cancer from spreading. Even after breast mastectomy, breast cancer may recur and still be a cause of death. A description of each of these imaging techniques is given below.

II. X-RAY MAMMOGRAPHY

X-ray Mammography is the most widely used medical imaging modality for early detection of breast cancer. X-ray mammography uses X-ray radiation in the frequency range of 30 petahertz to 30 exahertz (3×10^{16} Hz to 3×10^{19} Hz). It produces an image that is a projection of the entire breast (3D to 2D). Its spatial resolution of the mammogram image is approximately 20 lines pairs/mm. This method can detect approximately 78% of invasive breast cancer [4] and its sensitivity is as high as 98% in women over 50 years old with fatty breasts [4].

One of the major limitations of X-ray mammography is its low sensitivity in dense breasts. Mammograms of dense breast tissue common in younger women are difficult to interpret. Dense breasts are more likely to develop breast cancer and the sensitivity of mammography in these dense breasts can be low as 30%-48% [3]. Another disadvantage of mammography is the exposure of patients to the X-ray ionizing radiation, which may induce cancerous cells. In addition, the mammography screening process is sometime uncomfortable because the breast has to be compressed between flat surfaces to improve image quality.

breast cancer for the women with dense breast and it's more sensitive in women with dense parenchyma and premenopausal women and for those women who are under 50, [8]. However, digital mammography does not eliminate the fact that small, no calcified breast cancers can be obscured by dense parenchyma. Among almost 50,000 women who participated in the Digital Mammographic Imaging Screening Trial (DMIST), the overall sensitivity of screening mammography was only 55% [8]. With the errors approximately half of the cancers are visible in retrospect due to the lack of recognition of the suspicious nature of the lesion and by using double reading one can improve detection by 7% to 15% [9]. Physicians experience also plays an important role for detecting breast cancer in the early stage. Due to wrong interpretations sometimes breast cancer cannot be detected. Despite improvements and technological modifications done regarding mammography, still now at least 10% of breast cancers remain occult mostly for dense parenchyma [10]. For this reason, ultrasound imaging and magnetic resonance imaging have been used for further confirmation of breast cancer when screening a patient adjunct to mammography. For wider excisions and even mastectomies improved identification of disease extent is necessary.

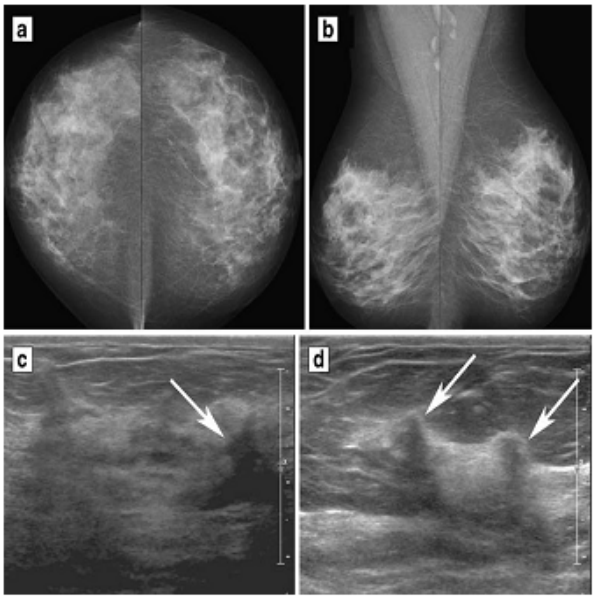

Fig.1. On mammogram images (a), (b) arrows shows a 7 mm (c) and 10mm (d), grade I, stage 1, invasive ductal carcinoma in situ on right and left breast respectively [5].

III. ULTRASOUND IMAGING

With ultrasound imaging, breasts are irradiated with sound waves through a probe containing an array of transducers. The frequency of sound waves is of 2- 20 MHz, which is much lower than the frequency range of X-ray, and, thus is safer. Ultrasound imaging systems produce images of single plane. These systems provide images in real time with a frame rate of detect breast cancers as small as 3 mm [4]. Recent studies suggest a predictive value of almost 98% for detecting invasive lobular carcinoma when both mammography and ultrasound imaging are used for screening [12]. In another recent study, 88% of invasive lobular carcinomas that were identified mammographically were also detected with ultrasound imaging [13]. Other studies showed that additional cancers where detected with ultrasound screening of women who had already been screened mammographycally. Results of a recent study show that with an increase in breast density, the detection rate of breast cancer also increases with the use of ultrasound screening.

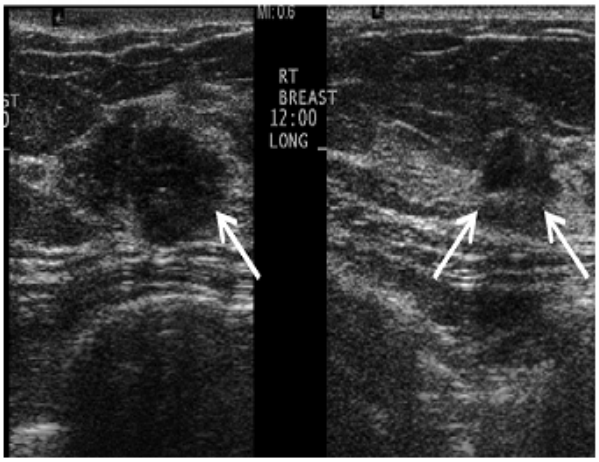

Fig.2. Longitudinal grayscale ultrasound images show two irregular hypoechoic masses (arrows), measuring 1.5 cm and 0.6 cm at the 10- and 12-o'clock positions respectively in the right breast. Ultrasound-guided core needle biopsies revealed intermediate grade ductal carcinoma in situ at both sites [4].

In a more recent study, women with heterogeneously dense and extremely dense parenchyma who had negative mammograms were found to have bilateral breast cancers when screened with ultrasound. Overall, ultrasound screening of mammographically negative dense breasts contributed to an additional cancer detection rate of 20% in asymptomatic women, compared with mammography alone, while maintaining a very low surgical biopsy rate (0.9%) [14]. The contribution was substantially greater for younger women than for older ones in the proportion of cancers detected (an additional 41.3% for under 50 years relative to an additional 13.5% over 50 years) [15]. These findings suggest that routine ultrasound screening in asymptomatic women might provide the greatest relative cancer detection yield if applied to women under 50 years of age with dense breasts [4].

Although ultrasound screening is very helpful in detecting breast cancer, in some cases it has a higher false positive rate and lower specificity. In addition, ultrasound imaging is highly operator-dependent, requiring real-time adjustments of gain, focal zones, dynamic range, pressure, patient positioning, and, most importantly, recognition of abnormalities. Therefore,

performed scanning using hand-held transducers will likely need to be changed [12].

Automated ultrasound imaging allows for reproducible image quality and consistency, and removes user variability [16]. However, there are limitations to using this technique because the resolution of the images obtained by most automated scanners is sometimes limited [16]. Furthermore, there is a learning curve with automated ultrasound imaging, as physicians need to gain familiarity with interpreting the data sets on a workstation. As vendors continue to improve image quality, automated breast ultrasound is likely to become a helpful tool for breast cancer screening [17].

Older technology enabled only differentiation of "cyst" versus "solid," whereas the higher-frequency transducers available today provide greater shape and margin definition, internal characteristics, and vascular patterns of solid masses such that better differentiation of benign and malignant is possible. Hence, further recommendations for biopsy or follow-up can be more confidently made.

Ultrasound also provides the best guidance method for biopsy of suspicious lesions in terms of cost, ease, and patient comfort. Use of ultrasound imaging can obviate the need for costlier stereotactic and MRI-guided procedures. As discussed previously, there are efforts being made to supplement mammography with other imaging tests in some women. Although those women at greater risk can be candidates for undergoing MRI, the majority, at low or intermediate risk, do not qualify. For these women, primarily those with dense tissue, screening with ultrasound imaging is suggested for early detection of breast cancer.

IV. MAGNETIC RESONANCCE IMAGING

Magnetic resonance imaging (MRI) is valuable tool for local staging before breast cancer surgery. Small invasive cancers and ductal carcinoma in situ can be detected using breast MRI due to remarkable advances in temporal resolution and spatial resolution [18]. For high-risk women, when supplemental screening is planned, MRI is performed in lieu of ultrasound imaging. The American cancer society has updated its breast cancer imaging guidelines and now advocates breast MRI for certain groups of high-risk women [22]. MRI imaging uses a large magnet of 3-5 Tesla and RF coils to produce 3D images of the breast. The signals received are processed to produce the images. Compared to other imaging techniques, MRI is relatively expensive and requires an intravenous injection of gadolinium, which causes the development of nephrogenic systemic fibrosis in a small group of patients with impaired renal function [23]. Therefore, a patient with a history of renal disease may not be able to undergo breast MRI. MRI also cannot be performed for breast cancer detection in patients who have pacemakers or any metal implants [24]. MRI imaging techniques are time-consuming and produce blurred images. Misinterpreted MRI images require that patients undergo the findings on MRI may prompt unnecessary excess tissue removal or in some cases unnecessary mastectomy.

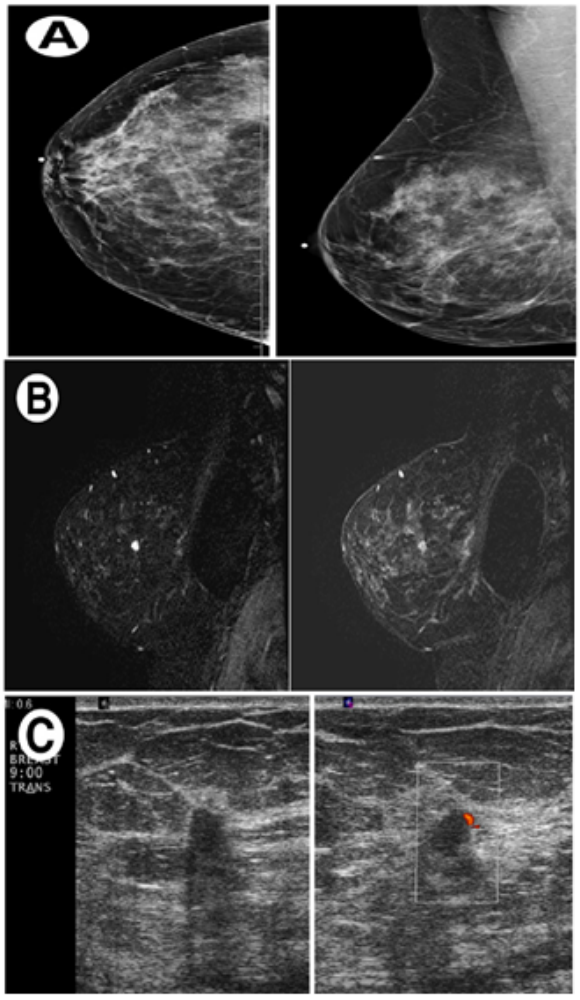

Fig.3. Annual mammography screening done upon a 59-year-old woman with a strong family history of breast cancer. No suspicious mammographic findings were identified. (B) Then the patient went through MRI screening on the same day and a 8-mm suspicious mass at the 9-o'clock position was found using MRI screening. (C) Later on transverse grayscale and power Doppler ultrasound images of the right breast in the 9-o'clock region show a corresponding 7-mm irregular mass with peripheral vascularity. Then Ultrasound-guided biopsy was performed, revealing evidence of invasive ductal carcinoma [4].

When lesions are identified, using MRI is a reliable method for biopsy or localization of breast cancer. Many breast biopsy systems are beginning to reach the market; however, they are hardly ubiquitous. From all the imaging techniques that have been investigated, MRI has the highest sensitivity for detecting invasive breast carcinoma and can provide valuable information that is not appreciated on the mammogram. Breast MRI screening is very encouraging when applied to high risk

V. CONCLUSION

In breast cancer screening, mammography still plays a major role. To detect early stage breast cancer, the individual patient's risk profile can serve as a good guideline for the entire screening process. Ultrasound can be a valuable adjunctive tool in the evaluation of lesions detected with mammography and clinical examination. MRI is recommended for women with a high risk of developing breast cancer. A combination of mammography, ultrasound, and MRI has shown to give very good results in detecting ductal carcinoma in situ and invasive cancer. Their combined use increases the likelihood of detecting breast cancer, and also reduces the rates of false detections. However, further improvements of these medical imaging techniques are needed in order to overcome current limitations and to increase their effectiveness in detecting breast cancer.

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