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# Fourier Transform Based Early Detection of Breast Cancer by Mammogram Image Processing

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**ABSTRACT**

Breast cancer is very common among the World's women population. Early detection of breast cancer can save life. Mammography based diagnosis is considered as the most effective to detect breast cancer. But, mammogram images often lead to misdiagnosis due to their low contrast nature. Recent studies show that mammography based diagnosis fails to detect cancerous lumps in the breast in ten out of one hundred patients. In this paper we address this issue. We propose a computer aided breast cancer detection technique in this paper. In the proposed method mammogram images are enhanced and segmented to locate the malignant lumps in the women's breast. The segmented image is then compared with a template image in order to determine the stage of breast cancer. Some statistical characteristics have also been presented in this paper to identify the malignant lumps from the benign ones.

***Keywords***: Breast cancer, calcification, image enhancement, image segmentation, edge detection, Fourier Transform

## 1 Introduction

Breast cancer is a most common cancer among the women. About two million new patients were diagnosed with the breast cancer in 2012. This represents 12% of all new cancer cases and 25% of all cancer in women. The North American countries are at the top of the list [1]. Out of 100,000 population 92 women in USA and 82 women in Canada [2] are affected by the breast cancer. Primarily breast cancer is considered as a hormone related disease. Recent studies show that there are also other factors related to breast cancer including excess alcohol consumption, age, family history, aged pregnancy, later menopause, smoking habit, dense breast tissue, radiation exposure, oral contraceptive, and obesity. The survival rate and prognosis differ greatly on the cancer stages. The cancer treatment is more effective provided the cancer is detected at the early stage.

The breast cancer can be detected by using imaging techniques. Some of the widely used imaging techniques are Magnetic Resonance Imaging (MRI), digital imaging, ultrasound imaging, nuclear imaging, bioelectric imaging, optical diffusion imaging, and mammogram imaging [3]. In MRI radio waves and magnetic fields are used to diagnose the breast cancer. In this method some kind of dye material is injected into the patient's body and reaction of the tumor tissue to this dye material is monitored. The main limitation of the MRI is the cost, which is five times more than that of X-ray mammography. In digital

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imaging a detector is used to absorb the X-rays in order to form an image. Some of the examples of digital imaging techniques include stereotactic imaging, full field digital mammography, single energy X-ray technique, 3D digital construction, tomosynthesis, and computer aided diagnosis. Among these imaging technique stereotactic imaging is the least expensive and widely accepted procedure. Other imaging techniques like full field digital mammography and 3D digital construction are still at their infancy level. Ultrasound and nuclear imaging techniques are also used to detect cysts in the breast. Some of the ultrasound imaging techniques include high frequency sonography, Doppler ultrasound, contrast imaging, sonoelasticity imaging, and guided biopsy. In nuclear imaging technique radioactive tracer is used to detect cyst in the breast. Position Emission Tomography (PET) imaging and Sestamibi scanning are the examples of nuclear imaging. Among these techniques the PET imaging is considered helpful for investigating the spread of a cancer. Other techniques like the sestamibi imaging is only helpful to detect large breast cancer and the bioelectric imaging is used for the early detection of breast cysts and pre-cancerous lesions. The bioelectric imaging is considered very effective to detect breast cancer in younger women, who have dense breast tissues. Optical diffusion imaging technique is also used to detect cancer. In this technique a near infrared light is used for probing the cancerous tissues in the breast.

Mammogram imaging is the most established and commonly practiced method for breast imaging. By using mammography the radiologists detect abnormal masses in the breast. But, there are some limitations of mammography. The quality of mammogram images depends on the density of the breast tissues. Moreover, the mammogram images have low contrast nature. Hence, there are always chances of 'false negative' and 'false positive' results. 'False negative' occurs more often among younger women than among older women. Because younger women have dense breast tissues. Breast tissues become somewhat less dense at the old age. 'False-negative' results can delay cancer treatment and promote a false sense of security. On the other hand 'false-positive' mammogram looks abnormal, but no cancer is actually present. 'False-positive' is also more common in younger women because of their dense breast tissues. It is also common among the women who have breast cancer in the family, or who are taking estrogen. 'False-positive' results incur further investigations. In this case diagnostic mammograms, ultrasound, and sometimes MRI or even biopsy are recommended in order to further investigate the presence of a malignant cancer.

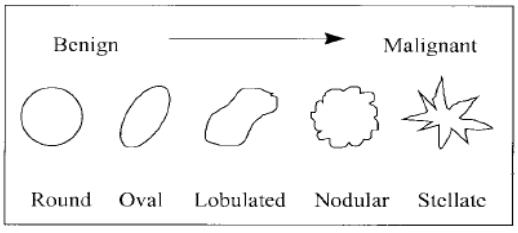


**Figure 1 Shapes of breast masses related to cancer stages**

The other limitations of mammography are associated with irregular shapes and locations of cancerous masses in the breast. There are different shapes that have been identified and published in the literature [4] as shown in Figure 1. It is already established that a well-defined round shape masses are considered benign and an irregular shape masses are considered malignant [4]. Sometimes the masses are hidden in the breast tissue and hence they are difficult to trace. In order to overcome these limitations computer aided detection is important. Computer aided detection can help the radiologists to detect and classify

the masses as benign or malignant. Computer Aided Detection can also reduce the variable interpretation of the masses by the radiologists.

## 2 Anatomy of Breast Cancer and Mammography

The female breasts, overlying the chest muscle, consist of two large hemispherical eminences that extend from the collarbone down to the underarm the body. The female breast is mostly made up of specialized tissues called adipose tissue. These tissues are a collection of fat cells. These tissues contain a network of ligaments, fibrous connective tissue, nerves, lymph vessels, lymph nodes, and blood vessels. These tissues also contain mammary gland as shown in Figure 2. Once stimulated by the birth of a baby the mammary gland secretes milk. There a number of sections in the breast called lobes. These lobes contain many smaller lobules. Both the lobes and lobules act as tubes to carry the milk to the nipple and are the sources of breast cancer.

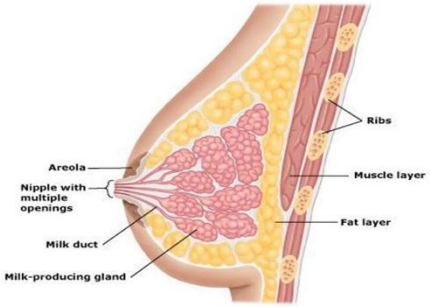


**Figure 2 Breast anatomy**

In the breast tissues there is a lymph system. The lymph system, consisting of lymph vessels and lymph nodes, is a part of an immune network system running throughout the entire body. The lymph system assists in transporting disease fighting cells and fluids similar to the blood circulation system of the body. Bean shaped lymph nodes filter abnormal cells from healthy tissues. Breast cancer occurs when lymph nodes fails to filter the abnormal cells. Breast cancer is generally originated from the growth of the abnormal cell (i.e., cancer cells) as shown in Figure 3. These abnormal cells grow almost always in the lobes, lobules, or ducts. By using imaging system radiologists try to find cancerous lymph nodes. After initial detection of abnormal cells the radiologist examine other nearby nodes for the presence or absence of cancer cells to investigate the extent of the cancer.

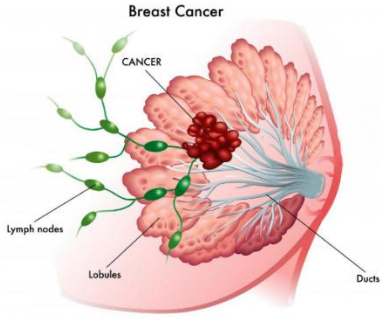


**Figure 3 Formation of Cancer in breast**

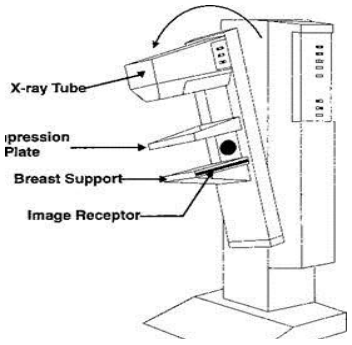


**Figure 4 Mammogram Machine**

Mammography is the most practiced imaging technique for detecting breast cancer. It is similar to an X-ray machine as shown in Figure 4. It uses a low amplitude and high current X-ray to examine the female breast. Ionizing radiation is used to create breast images in mammography. These images (i.e., mammogram images) are than analyzed for examining the existence of masses in the breast. Once the radiologists detect some abnormal masses in the mammogram images, they recommend other techniques for further investigations. Ultrasound, ductography, positron emission mammography (PEM), and magnetic resonance imaging (MRI) are the examples of such techniques. Among these techniques ultrasound is typically used for further investigation of the masses detected by mammography. Ductograms are used for investigation of bloody nipple discharge, which is usually related to breast cancer. MRI is useful for further investigation of additional lesions in the breast. In order to detect the cancer (i.e., microcalcification) in the breast a high resolution mammogram image is required. But, the quality of a mammogram image highly depends of the breast tissue density. To capture a better images two methods namely craniocaudal and mediolateral oblique are used in mammography. The craniocaudal is used for better imaging the inner and central breast sector. On the other hand mediolateral is used to better imaging the glands. In order to improve the quality of the mammogram images some other properties of images including magnifications, brightness, orientation, and contrast are adjusted. It has been claimed in [3] that mammogram imaging can detect about 85% of the breast cancer. It has also been claimed in the same work that mammogram image can help to detect breast cancer at early stage and hence can reduce the mortality rate by 50%.

Although mammography is considered as the most reliable methods for breast cancer detection, it has some limitations too. Some of the limitations are listed as follows: (a) reading mammogram images highly depends on the radiologists' skill, (b) mammogram images may appear normal even though breast cancer is present, and (c) mammogram images may fail to detect cancer for the patients with dense breast tissues. Due to these limitations mammogram screening fails to detect cancer in the breast.

## 3 Related Works

Detection of breast cancer is not a new idea. Since the 16th century medical research has targeted breast cancer detection and diagnosis. But, breast cancer detection was an illusion that time due to lack of medical technological developments. Since then numerous developments and innovations have been done in this field. New tools have been developed including medical image processing. With the help of medical image processing it has become easier to detect masses in the breast. Digital mammography is

playing an ever increasing important role in detecting breast cancer and hence in reducing the mortality rate. Image processing techniques have been introduced and being used to detect abnormal features in breast mammogram image. Some of the abnormal features include microcalcifications, masses, bilateral asymmetry, and architectural distortion. With the help of digital mammography and digital image processing early detection of breast cancer is now very common.

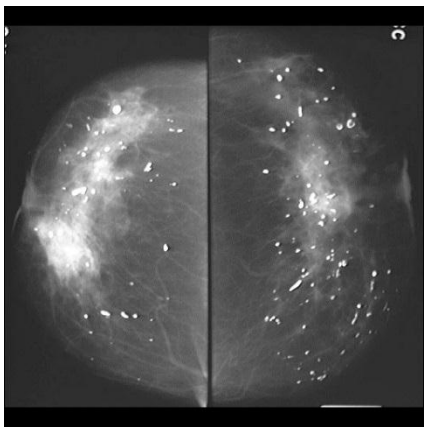

**Figure 5 Mammogram images with calcifications**

While detecting the breast cancer at its early stage the radiologists try to detect microcalcifications in the mammogram images because there is a high correlation between the microcalcifications and breast cancer. The size of microcalcifications may vary in the range of 0.00 mm to 1 mm. Due to this small size mcirocalcifications are very difficult to detect. In addition the distribution and shapes of the microcalcifications vary widely [5, 6] as shown in Figure 5. The low contrast nature of these microcalcifications with respect to their surrounding tissues causes problem for the radiologists to detect them. Many researches have been conducted to accurately detect these kind of microcalcifications.

An image enhancement technique based on wavelet transform and adaptive histogram equalization has been proposed in [7]. The proposed method consists of three steps namely (a) image enhancement, (b) image segmentation and (c) border extraction. The authors have proposed a region growing method for detecting microcalcifications in the breast. The method has been experimented on four patients. The results show that the proposed method is very effective in detecting cancerous masses in the breast.

The detection of microcalcification clusters has been introduced in [8]. By using image processing, pattern recognition, and artificial intelligence the authors have successfully detected microcalcification clusters with a very high accuracy. The authors have enhanced mammogram images by using morphological operation. Then they have detected microcalcification clusters by a K-mean algorithm. In the last step the authors have classified cluster by a neural network based classifier.

A similar wavelet based calcification has been presented in [9]. In this work the authors have claimed that microcalcification corresponds to a high frequency components in the mammogram image. They have proposed a technique to decompose an image into low frequency sub-band and high frequency sub-band. Then they have eliminated low frequency sub-band and have reconstructed the image from the high frequency sub-band. The authors have used a novel image segmentation techniques called 'Pyramid' segmentation to detect the masses.

Breast cancer detection by investigating bilateral asymmetry has been presented in [10]. The bilateral asymmetry has been detected by using B-spline interpolation for breast alignment. In this work the alignment of the right and left breast has been accurately determined so that the radiologist can perform further investigation to detect cancer.

In another similar work [11] the correlation between the breast asymmetry and breast cancer has been investigated. Segmented breast volume has been used to measure the asymmetry between two breasts. The proposed system has been used to diagnose the breast cancer in 350 patients. The authors have observed that cancer patients have more asymmetry in the breasts compared to normal patients. The authors concluded that bilateral breast volume asymmetry is a good tools in order to identify the patients with a risk of breast cancer.

A region growing segmentation technique has been proposed in [12] in order to detect breast cancer. In this work pre-processing of mammogram image has been performed by a selective median filter. Contrast Limited Adaptive Histogram Equalization has been used to enhance the image. Finally, the Harris Corner detect algorithm has been used to detect the growing region of the cancer. They authors have also introduced a new uncertainty theory called 'Cloud Model' for automatic selection of segmentation threshold.

Importance of breast cancer feature extractions has been addressed in [13]. The authors have investigated different mammogram images to find important features of them. They have defined some ranges of these features so that radiologist can detect cancer depending on these ranges.

Effective identification of the masses in breasts has been presented in [14]. In order to verify the existence of the masses in the breast an optimal selection method has been proposed in [15]. The selection method is based on some important features like textural, intensity, and shape extracted from the mammographic images. These features have been used for detecting masses in the breast. The authors have also proposed a novel wavelet based feature extraction method in the paper.

A Particle Swarm Optimization (PSO) technique has been used in [16] to identify and locate the cancerous masses in mammogram images. The authors argued that the masses in a mammogram image has low frequency component and hence they are hard to detect. The authors have proposed a method to enhance the low frequency mass signal by using wavelet transformation. Then the possible masses are detected by using PSO algorithm. The authors tested the proposed method and concluded that their method can detect masses with an accuracy of 94.44%.

In this paper we also propose a new method of detecting and analyzing the breast cancer. The proposed method of breast cancer detection are performed in mainly three stages namely (a) initial screening, (b) image enhancement, (c) edge detection, and (d) template matching. The mammogram images are initially screened to determine the existence of masses in the breast. Once it is ensured that there is some masses further investigations are performed in the remaining stages. By using image enhancement and image segmentation the concerned masses are separated from the rest of the mammogram image. Then the edges of the mass are detected. In the last stage template matching is performed in order to determine the cancer stage. In the template matching step we use Fourier transform method. In the early stage of breast cancer it is hard to distinguish between the benign masses and cancerous masses. Hence, we have presented some statistical analysis in this paper that help to overcome the above mentioned limitation.

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# 4 Proposed Method of Analysis

In this work we consider three sample mammogram images namely (a) normal breast, (b) breast with benign masses, and (c) breast with malignant masses. These three images are shown in Figure 6(a). In order to visualize the cancer affected area we created 3D images by using available MatLab function.

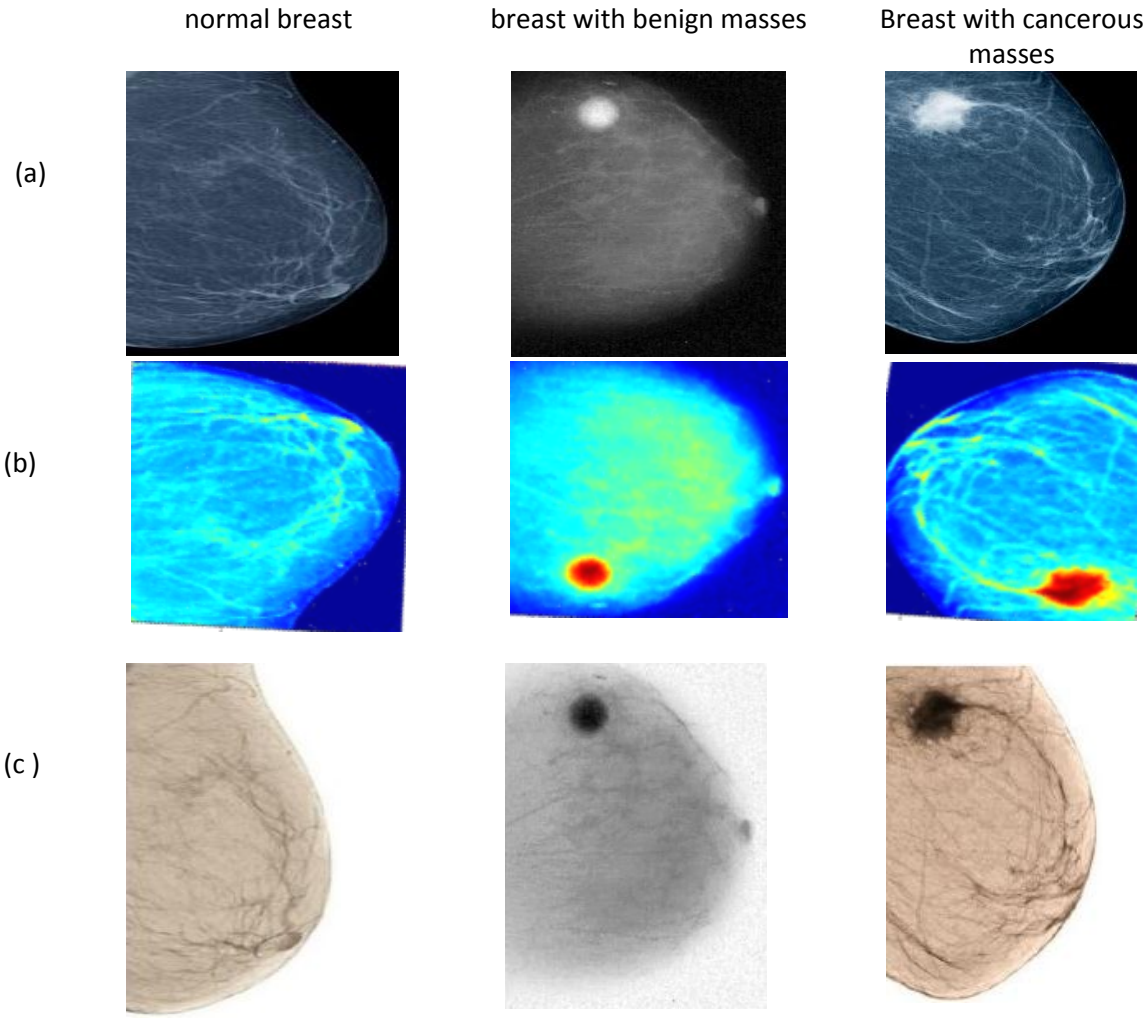



**Figure 6 Sample images (a) mammogram images, (b) 3D visualization (rotated), (c) masses and tissues of normal, benign and cancerous condition.**

The 3D images are shown in Figure 6(b). It is worthwhile to mention that the 3D images have been rotated for better visibility. It is depicted in Figure 6(b) that the 3D images are very helpful to find the location, shape, and extent of the masses in mammogram images. This figure also shows that the benign masse has more regular shape (i.e. circular). On the other hand the malignant masses have irregular shape. Finally, the complement of the original mammogram images is created by applying appropriate threshold. The complemented images are shown in Figure 6(c). The complementary images are very helpful to identify the tissues in the breasts. It is also helpful to find the location of the masses in the breast tissue.

In order to distinguish primitives of a malignant mass and a benign masses we focus on some image features including histogram, probability density function, autocorrelation, covariance, mean, standard deviation, skewness, kurtosis, and entropy. Some of these features are based on the first-order probability

density function of the pixels and the others are based on the second-order probability density function of the pixels. These features are important to separate the malignant masses from the benign masses at the early stage of cancer. The mean and standard deviation are computed directly from the histogram of image pixels based on the first-order probability density function defined as

$$p(b) = P_R[F(j,k) = r_b] \tag{1}$$

where $r_b$ denotes the quantized amplitude level for $0 \le b \le L-1$. The first order histogram estimate of p (b) is simply expresses as

$$p(b) = \frac{N(b)}{M} \tag{2}$$

where M represents the total number of pixels in a neighborhood window centered about F(j,k), and N(b) is the number of pixels of amplitude $r_b$ in the same window. The histograms of the mammogram images with benign and malignant masses are presented in Table 1. This table shows that the histogram of malignant mass is narrowly distributed. On the other hand the histogram of mammogram image with benign mass is bimodal. The other quantitative measures of the images are defined as follows:

Mean
$$\bar{b} = \sum_{b=0}^{L-1} bp(b) \tag{3}$$

Standard Deviation
$$\sigma_b = \left[\sum_{b=0}^{L-1} (b-\bar{b})^2 p(b)\right]^{1/2} \tag{4}$$

Skewness
$$S = \frac{1}{\sigma_b^3}\left[\sum_{b=0}^{L-1} (b-\bar{b})^3 p(b)\right] \tag{5}$$

Kurtosis
$$K = \frac{1}{\sigma_b^4}\left[\sum_{b=0}^{L-1} (b-\bar{b})^4 p(b)\right] - 3 \tag{6}$$

Energy
$$E = \left[\sum_{b=0}^{L-1} [p(b)]^2\right] \tag{7}$$

Entropy
$$E_n = -\left[\sum_{b=0}^{L-1} [p(b)\log_2 p(b)]\right] \tag{8}$$

The covariance and autocorrelation are second-order histogram features. These are determined by the joint probability distribution of pairs of pixels. The joint probability is defined by

$$p(a,b) = P_R[F(j,k) = r_a, F(m,n) = r_b] \tag{9}$$

where F(j,k) and F(m,n) are two pixels located at the coordinates (i,j) and (m,n), $r_a$ and $r_b$ represent two quantized pixel amplitude value. The histogram estimate of the second order distribution is defined as

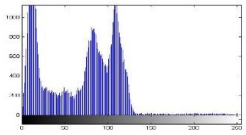
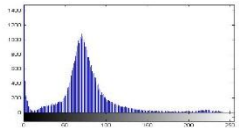
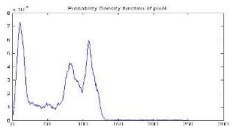
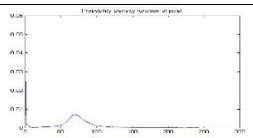
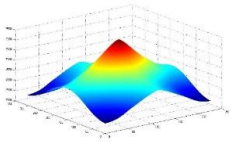
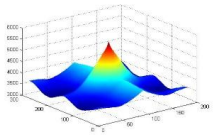
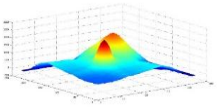
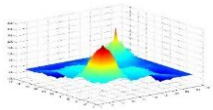
$$p(a,b) = \frac{n(a,b)}{M} \tag{10}$$

where M is the total number of pixels in the measurement window and n(a,b) denotes the number of occurrence for which $F(i,j)=r_a$ and $F(m,n)=r_b$. Based on the definitions the other two features are expressed as follows:

Autocorrelation $$S_A = \sum_{a=0}^{L-1}\sum_{b=0}^{L-1} abp(a,b) \quad (11)$$

Covariance $$S_C = \sum_{a=0}^{L-1}\sum_{b=0}^{L-1} (a-\bar{a})(b-\bar{b})\,p(a,b) \quad (12)$$

**Table 1: Comparison between benign and malignant breast masses**

| Parameter | Breast with benign masses | Breast with malignant masses |
|---|---|---|
| Histogram |  |  |
| PDF, p(b) |  |  |
| Autocorrelation, $S_A$ |  |  |
| Covariance, $S_C$ |  |  |
| Mean, b | 22.7367 | 20.8688 |
| Standard deviation, $\sigma_b$ | 36.1298 | 34.7059 |
| Skewness, S | 2.5027 | 2.8734 |
| Kurtosis,K | 4.3040 | 8.1524 |
| Energy,E | 0.0012 | 0.0041 |
| Entropy,$E_n$ | 6.8352 | 6.2177 |

The above mentioned image features of benign and malignant masses are listed in Table 1. This table shows that the mammogram image with malignant masses have very sharp peaks in the autocorrelation and covariance. Among other parameters kurtosis, standard deviation and entropy of the malignant masse are significantly different that those of the benign masse.

The mammogram images need to be enhanced so that the masses can be separated from the rest of the mammogram image. In order to enhance mammogram image we follow the steps shown in Figure 7. In the first step we pre-process the image and convert the image into a binary image. The other major steps are converting the color image into a grey image, filtering the image by Gaussian filter, and applying a threshold to separate the masses from the rest of the breast image.

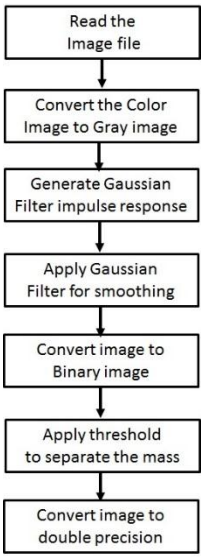



**Figure 7 Image processing steps to separate the masses**

Then the image was converted into logarithmic scale by

$$I = \log(1 + I) \tag{13}$$

In order to perform smoothing operation a Gaussian filter was used, whose impulse response is defined by

$$H(x,y) = e^{-\left[\frac{(x-\mu_x)^2+(y-\mu_y)^2}{2\delta^2}\right]} \tag{14}$$

where $\mu_x$=ceil(N/2) and $\mu_x$=ceil(M/2), $\delta^2$= variance, M=2*size(I,1)+1, N=2*size(I,2)+1, and I(i,j) is the image pixel. The Fourier transform of the Gaussian filter is given by

$$H(m,n) = \sum_{x=1}^{M-1}\sum_{y=1}^{N-1} H(x,y)e^{-(\frac{2\pi}{M}x+\frac{2\pi}{N}y)} \tag{15}$$

The magnitude plot of H(m,n)(dB) is shown in Figure 8. Since the most of the frequency components of an image in the low ranges, we select a Gaussian filter with a very narrow bandwidth. The filtering of the image is done by the convolution operation defined by

$$I_{out}(p,q) = F(l,k)H(m,n) \tag{16}$$

where F(l,k) is the Fourier Transform of the image determined by

$$F(l,k) = \sum_{i=1}^{M-1}\sum_{j=1}^{N-1} I(i,j)e^{-(\frac{2\pi}{M}i+\frac{2\pi}{N}j)} \tag{17}$$

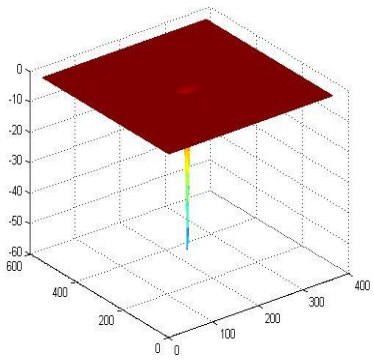
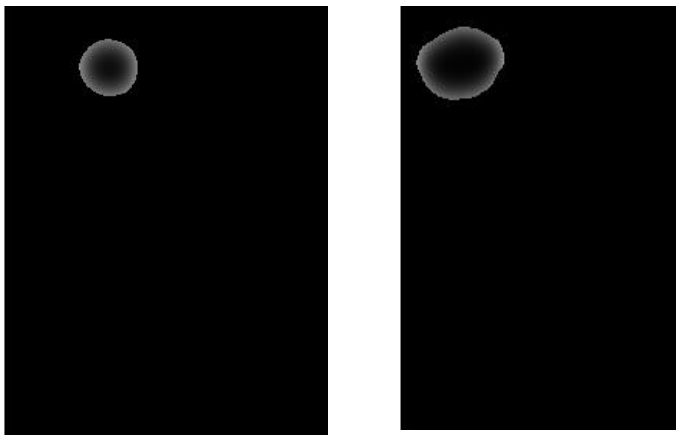



**Figure 8 The Spectrum of the Gaussian Filter**

Then the output image was generated by the inverse Fourier Transform of $I_{out}(p,q)$ . The output images of the breast with benign masse and with malignant masse are shown in Figure 9. It is depicted in this figure that the benign mass has a regular shape, but the malignant mass has an irregular shape.



(a) Benign mass (b) Malignant mass

**Figure 9 The output images produced by the algorithm**

In order to determine the stage of the cancer we need to detect the edges of the image produced in the previous step. The edge detection is done by the algorithm shown in Figure 10. The segmentation

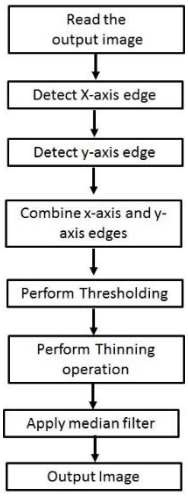



**Figure 10 Image processing steps for detecting the edges**

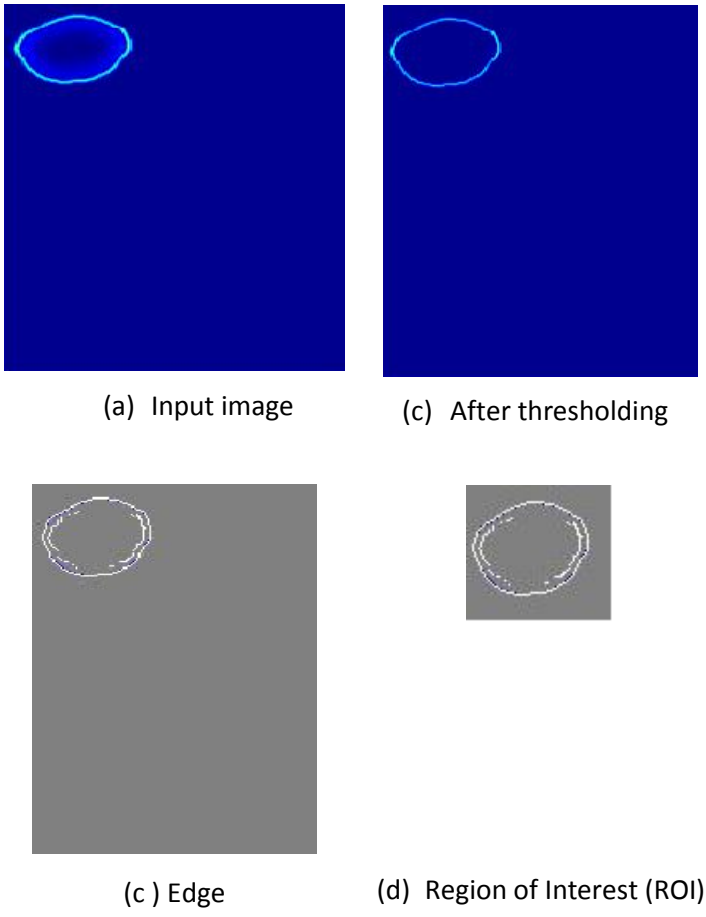



**Figure 11 Images produced by the algorithms of edge detection**

process is done in two major steps namely (a) horizontal edge detection, and (b) vertical edge detection. These two edge components are then combined to produce the total edges of the image. The edges of the image are now separated by using appropriate threshold operation. The final edge detection is

performed by using MatLab provided boundary function. The output images of the above mentioned steps are shown in Figure 11. Finally, the MatLab provided function ROIPOLY function has been used to separate the region of interest from other part of the image. Now. The image only contains the edges of the mass. The generated edges of the image are now ready for matching in order to determine the cancer stage.

## 5 Method of Matching

There are numerous methods that have been proposed in the literatures for matching a given image with the images contained in a template. In this work we have used Fourier transform method. The Fourier transform method of matching takes the advantages of duality property of Fourier transform, which relates convolution in frequency domain with multiplication in time domain. Let us assume that **I** is the input image data and **T** represents template image data. The correlation of these two signals are defined as

$$I \otimes T = \sum I_{x',y'} T_{x'-i,y'-j} \tag{18}$$

where *x'=x+I* and *y'=y+j.* The correlation can be related to the convolution by using

$$I \otimes T = I * T' = \sum I_{x',y'} T_{i-x',j-y'} \tag{19}$$

where $T'=T_{-x,-y}$. In the frequency domain convolution corresponds to multiplication. The T' can be obtained by flipping the template image. In the frequency domain the convolution becomes multiplication and it can be implemented as

$$I_{output} = I \otimes T' = F^{-1}\left(F(I)F(T)\right) \tag{20}$$

```
% Template matching algorithm
Read the input Image
Read the template image and flip it
% Determine the image size
[x_input, ,y_input]=size(inputimage);
% Apply the Fourier Transform on the input image
FT_image=fft(inputimage, x_input,y_input);
% Apply the Fourier Transform on the template
FT_template=fft(templateimage, x_input,y_input);
% perform the convolution (which is multiplication in frequency domain)
FT_output_image=FT_image*FT_template;
% Apply Inverse Fourier Transform to find the output image
Output_image=real(IFFT(FT_output_image));
```

**Figure 12 Algorithm for template matching**

The Fourier Transform of the image and the template image can be quickly computed by using the Fast Fourier Transform (FFT) algorithm. It is worthwhile to mention that the size of the image and template are usually not the same. This limitation is overcome by including extra zero values (zero-padding) with the template. The rest of the template matching algorithm is shown in Figure 12. The image $I_{uotput}$ is shown in the Figure 13. The output image shows a white vertical bar to indicate the maximum matching of the image with the template image. The location of the bar shows that the shape of the segmented mass in neither a circular nor an oval. It means that the cancer stage is still in the early stage. The mass has just started forming an oval shape.

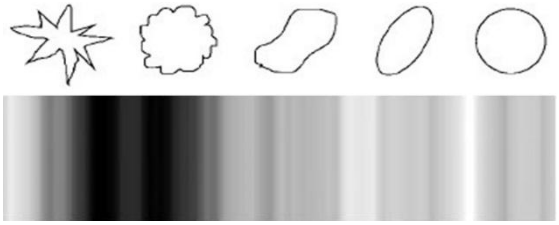


**Figure 13 Output image show the cancer stage**

## 6 Conclusions

In this paper an early breast cancer detection system has been presented. Although mammogram images are used for cancer screening, it has some limitations due to its low contrast nature. Moreover, early detection of breast cancer is not straight forward. In the early stage of cancer it is very difficult to separate the malignant masses from the benign masses. Because both of the masses have almost similar shape. In order to separate them more image features need to be investigated. In this paper we have proposed an early stage cancer detection system. The proposed system overcomes the above mentioned limitations. The proposed system consists of four stages namely initial screening, statistical characterization, edge detection, and template matching. In the initial screening the mammogram images are investigated to discover any abnormal masses in the breast. Once abnormal masses are found more comprehensive statistical analysis is done. Finally, the edges of the mass is detected and is matched with a template. By using Fourier transform method it has been shown that our proposed system can successfully detect the stage of breast cancer.

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