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Analysis of Tumor Detection Methods for Mammogram Images

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Abstract—Breast cancer remains the important reason of death among woman in the world. Early detection is essential to improve breast cancer diagnosis. Mammography is the reliable and best existing tool for investigation of breast cancer in its early stage. Understanding the mass region information of cancerous lesions in a mammogram is important for detection of the tumor region and its segmentation. In this paper, Maximum Mean and Least Variance method and Otsu method is implemented and then compared the results to find the suitable technique among them for detection and segmentation of tumor region.

Keywords—Breast cancer detection, Mammograms, Smoothing, Segmentation, Enhancement, Masses, Microcalcification

I. INTRODUCTION

In the present days, one of the most threatening diseases faced by the women across the globe is breast cancer [1]. Though it is possible to treat this cancer in its initial periods still the mortality rate is not declining [2]. According to reports, the second most important cause of death among the women worldwide is breast cancer around 22% and in India around 18.5%. This problem is rising both in developed and developing countries. Studies have discovered that breast cancer mostly occur in women above the age of 50 in developed countries whereas for Indian women the age is above 40 years [3]. According to the world health organization's International Agency for Research on Cancer (IARC) more than 400,000 women lose their lives every year due to breast cancer [4]. A report also predicted that during lifetime one in eight women in U.S. and one in thirteen women in Australia develop breast cancer [5]. Therefore, early discovery and treatment of the cancer is essential in order to decrease the mortality rate. The key to improve breast cancer diagnosis is through early detection. According to the five years report, early detection of tumors using mammogram images increased the survival rate for women by 82% as compared to 60% that failed to detect early [6].

Mammography is one of the best approaches for discovery of cancer in its initial stage [7]. But the appearance of breast cancers are very elusive and uneven in their initial phases. In a mammogram, cancer is represented by a region which is brighter than the nearby regions. It is possible to find the existence of both malignant and normal regions in some mammogram images. Applying thresholding alone it is not possible to differentiate between them. Therefore, it is important to understand cancerous lesions information in an image which is helpful in identifying the regions of the tumor [8].

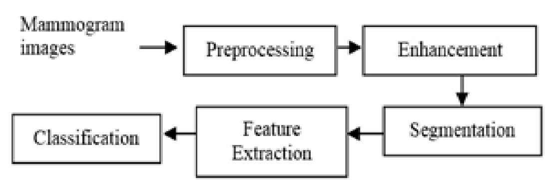


Figure 1. A Digital Mammography System

Figure.1 represents a typical diagram of a digital mammography system. Mammograms are digitized with different sampling and quantization rates in the pre-processing stage. Then the selected region of interest from the mammogram is enhanced and noise is removed. The segmentation stage is designed to separate the suspicious cancer region from the background. Then features are extracted from the cancer region and then it is classified into benign, malignant and normal [6].

Cancerous lesions are grouped as microcalcification and space occupying based on the breast cancer representation in mammograms [5]. Microcalcifications are very small and ranges between 0.1 to 1.0 mm. They are of various shapes and sizes but may be of low contrast so it is very difficult to differentiate between suspicious areas and their surrounding tissues [6]. Space occupying lesions are divided into masses, architectural distortion and asymmetry. Amongst them, masses and architectural distortion are distinctive signal features of breast cancer. Figure.2 depicts the diagrammatic representations for the classification of cancerous lesions.

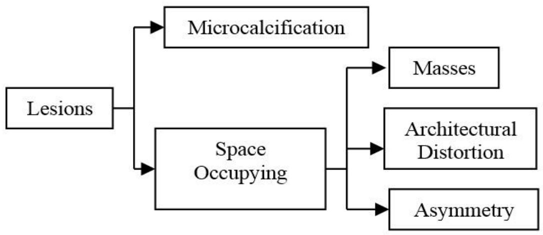


Figure 2. Classification of Cancerous Lesions

Masses are described by the properties such as shapes, margin, density etc. According to reports, depending on shapes a mass divided on a mammogram image can be benign or malignant [9]. Benign tumors are of round or oval shape while malignant tumors have a partially rounded shape with an uneven outline. Table I depicts the characteristics of masses.

Table. Characteristics of Masses [10]

Characteristics	Types	Classes
Shape	Round	Likely Benign
	Oval	Likely Benign
	Lobular	Likely Benign, Suspicious
	Irregular	Highly Suspicious of Malignancy
Density	Quite fatty	Likely Benign
	Low	Likely Benign
	Iso	Likely Benign, Suspicious
	High	Highly Suspicious of Malignancy.
Margin	Well-defined	Likely Benign
	Obscured/ 75 % hidden or more	Suspicious
	Micro lobulated	Suspicious
	Indistinct and ill-defined	Suspicious, Highly Suspicious of Malignancy
	Spiculated	Highly Suspicious of Malignancy

Several techniques have been employed for the discovery of malignant area in mammogram images. It is necessary to segment properly the malignant regions in mammogram images in order to have a better detection. In this paper, we focus on cancer region detection and then segmenting the region surrounded by malignant tissues. In this context, two existing methods i.e. Otsu method and Max-Mean and Least-Variance technique is implemented and the results are compared to find which method among them provides a better segmentation of the cancerous region.

The organization of the paper is as follows. Section I contains the introduction of cancerous lesions and digital mammography, Section II explains few of the conventional enhancement techniques, Section III explains the commonly used segmentation techniques, Section IV contains the data collection, Section V explains the Otsu method, Section VI describes Maximum Mean and Least Variance Method, Section VII gives a comparison of the above methods and Section VIII concludes the work performed.

II. CONVENTIONAL ENHANCEMENT TECHNIQUE

This techniques are mostly based on the global and fix neighborhood methods. In the fix neighborhood method, the image is adjusted according to the local characteristics and then based on the global properties only the image is transformed. The histogram equalization, adaptive histogram equalization and CLAHE are the main techniques [6].

A. Histogram Equalization

It is a method which produces a gray mapping that deviates an image histogram and reorganize the values of all the pixels as a user desired histogram. It permits the area with low contrast to have a high contrast. Equalization of the histogram accordingly defines a function for the transformation to generate an identical histogram of the output image. This technique increases the overall contrast of several images, particularly when the image data is characterized by the values of contrast which are related closely [11].

B. Adaptive Histogram Equalization

This method is used for improving the contrast of an image [12]. There are different ways in which Adaptive Histogram Equalization process can be understood. One perspective is that the grey levels histogram is generated first in a window around each pixel. To map the input grey level pixel to output grey level pixels cumulative distribution of grey levels is used. The output is extremely black if a grey level pixel has value less than the window enclosing it. If the grey level pixel has a median rate in the surrounding then the result is grey by 50% [13]. It increases noise in an image.

C. CLAHE(Contrast Limited Adaptive Histogram Equalization)

This technique is used for enhancing the contrast of the images in the medical domain. The image is divided into contextual regions using the CLAHE algorithm and histogram equalization is applied to each of them. For contrast maximization of all the pixels in an image, CLAHE algorithm transforms the image intensity values using a nonlinear method. It makes the hidden features of the image further observable and evens out gray distribution values. But histogram equalization comprises the probability of enhancement of noise, which results in the degradation the original image quality [14].

III. Commonly Used Segmentation Technique

Medical application requires the help of image segmentation for simplifying the description of functional arrangements and other regions of relevance [15]. Thresholding and region growing segmentation method is discussed below.

A. Thresholding

It is a basic but constructive means for achieving image segmentation where various structures have contrasting intensities [15]. This method uses binary partition of the intensities to obtain the segmentation of the scalar image. A thresholding technique defines an intensity value known as the threshold and then segment by grouping all pixels higher than the threshold into one class, and the other pixels into different class. Though automatic segmentation methods are present still the partition is generally produced interactively. Thresholding is often the initial stage in image processing application. The limitation of thresholding method is that spatial characteristics of an image is not taken into account which causes the image sensitive to noise. This makes separation difficult because the histogram image is corrupted.

B. Region Growing Method

This is a method for obtaining an image region that is linked based on certain predefined standards [15]. This standards can be established on intensity data and image edges. Region growing algorithms needs a seed point which is selected manually by an operator, and all pixels linked to the original seed are extracted with the value identical to the intensity. This algorithm is used within a set of image processing operations, mostly for the description of minor, simple arrangement such as tumors and lesions. Its main drawback is that to find the seed point it requires manual interaction. Thus, a seed needs to be established for each region that must be obtained. This algorithm can too be subtle to noise resulting extracted regions to have holes or become disconnected.

IV. Data Collection

The mammogram database used in our experiment is Mammographic Image Analysis Society (MIAS) Mini Mammographic Database [16]. This database has been used as a standard database in various research work performed earlier. Every image in MIAS database is of size 1024 x 1024. There are total of 322 cases in the database, out of which 207 cases are considered normal while the other 115 cases possesses some form of abnormalities. Out of 115 cases, it consists 54 cases of benign and 61 cases of malignancy [16].

V. Otsu Method

This method is simple, efficient and easier to implement. Choosing the optimal threshold is done automatically [17]. Otsu's algorithm is summarized in the following steps [18].

- Calculate the standardized histogram of the chosen image. Represent the histogram elements by P_i , where i = 0, 1, 2, …. L -1.
- Calculate the total sum, $P_1(k)$, for k = 0, 1, 2, ……, L-1, using $P_1(k) = \sum_{i=0}^{k} p_i$
- Calculate the total sums, m(k), for k = 0, 1, 2, ……, L-1, using $m(k) = \sum_{i=0}^{k} ip_i$
- Calculate the mean of overall intensity, m_G using $m(G) = \sum_{i=0}^{L-1} ip_i$
- Calculate the relating class variance, , for σ^2(k), k=0, 1, 2,…..,L-1,using $\sigma^2 = \frac{[m_G P_1(k) - m(k)]^2}{P_1(K)[1-P_1(K)]}$
- The Otsu threshold, k*, is obtained as the k value for which $\sigma^2(k)$ is maximum. k* is obtained by averaging the k values related to the several identified maxima if the maximum is not unique.
- Get the measure of separability, n* by calculating $n(k) = \frac{\sigma^2(k)}{\sigma_G^2}$ at k= k*

VI. Maximum Mean And Least Variance Method

This technique employs simple but proficient method for recognizing the cancer region in a mammogram. In this approach, the affected region is segmented from the input mammogram successfully. Figure.3 depicts a brief summary of Maximum Mean and Least Variance technique [8].

In the following step, the Maximum Mean and Least Variance is described in detail [8].

- An input mammogram image of size M x N is taken.
- To smoothen the pixels having intensity similar to the pixels of the cancerous region average filter technique is performed.
- The cancer region pixels is separated from normal region using a threshold value. The thresholded value is calculated manually. A white blotch surrounding the cancer region is found after thresholding.
- Then a window rectangular near the white blotch is created to cover the whole region and this window is employed to the original image.

- A sub window s x s is created after dividing the rectangular window. The local mean and variance of each sub-window is calculated. Considering that cancerous region pixels consists of higher pixel value than normal region, the highest mean and least variance is found in the sub windows.
- Thereafter, the cancer region is segmented from the input mammogram image.

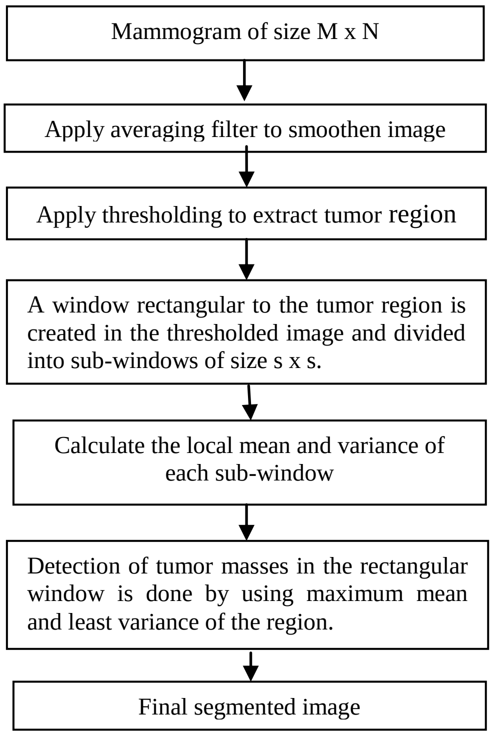
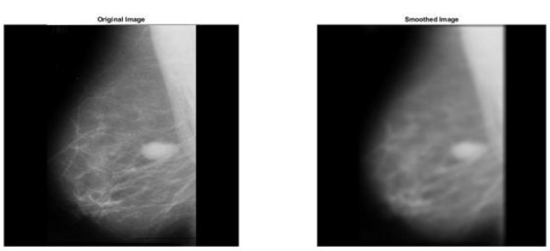


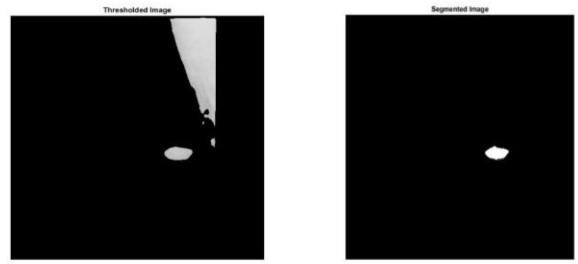
Figure 3. Maximum Mean and Least Variance Technique

VII. Comparison

Applying the two techniques on the same image we find the results as follows.



(a)Original Image (b) Smoothed Image



(c) Thresholded Image (d) Segmented Image

Figure 4. Segmentation and detection result on mammogram image mdb025 using Max-Mean and Least-Variance Technique

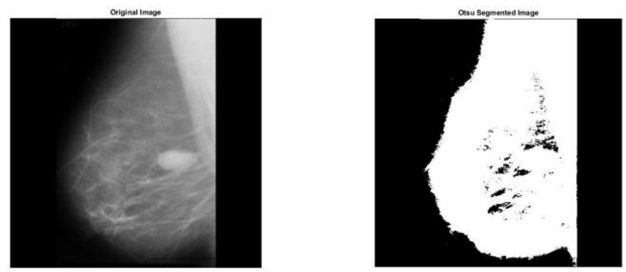


Figure 5. Segmentation result on mammogram image mdb025 using Otsu method

VIII. Result And Conclusion

It is distinct from the results that applying maximum mean and least variance method, detection and segmentation of the cancerous region is done successfully than the Otsu method. It is also difficult to identify the cancer region in the image segmented using the Otsu method. The drawback of the Maximum Mean and Least Variance technique is that threshold value is selected manually.

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